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Evans, Debra C.; and Roth, J. Thomas (Applied Science Associates, Inc.)

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Debra C. Evans and J. Thomas Roth

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for

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DEVELOPMENT OF A METHOD FOR THE ASSESSMENT OF MANPOWER, PERSONNEL, AND TRAINING IMPLICATIONS OF MAINTENANCE REQUIREMENTS

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DEVELOPMENT OF A METHOD FOR THE ASSESSMENT OF MANPOWER, PERSONNEL, AND TRAINING IMPLICATIONS OF MAINTENANCE REQUIREMENTS

INTRODUCTION

Of the many difficult aspects of systems procurement facing the U. S. Army today, one of the greatest challenges is the determination of relationships that exist among manpower availability, personnel characteristics and skills, training requirements, training methods, and system aspects, as they impact the ability to perform maintenance for the system. Each of these factors, by itself or in concert with others, could potentially radically impact aspects of expected system maintenance requirements and actual maintenance. To assure a strong maintenance function to support the complexity, sophistication and capabilities of today's military systems, the Army must develop methods for validly estimating the maintenance requirements for a new material system early during system acquisition.

Within recent years the U. S. Army Research Institute for the Behavioral and Social Sciences (ARI) has been supportive of the MANPoweR INTegration (MANPRINT) program by conducting research and developing methods to evaluate and project manpower, personnel, and training (MPT) requirements for new and existing systems. Several of these efforts, for example HARDMAN III, have included methods to clarify and define the relationships among maintenance performance, MPT, and system factors, and to estimate their impact on maintenance. Due to the recency of these efforts, no systematic attempt has been made to establish the relationships among all of the on-going efforts. Such integration is necessary in order to understand the importance of the various programs in relation to each other and to the overall system procurement and management process and to develop a common language or context by which to view these endeavors.

This report represents the culmination of a three phase exploratory effort to examine the relationships among MPT and system factors as they impact maintenance planning and performance. The goal for Phase 1 was to examine the factors that appear in eight models resulting from ARI-sponsored efforts that portray MPT and system factors which impact maintenance burden (or the ability to perform maintenance) and define the relationships and any apparent structure among these factors. This definition of relationships and structure resulted in a framework in which future efforts can be placed, as well as elucidated the relationships among current efforts. The details of this work may be found in Evans, Roth, and Hogg (1990).

Phase 2 had two goals. The first goal was to develop weights and confidence ratings for defined MPT requirements (factors) which impact maintenance performance. The relationships among these requirements are described in Evans and Roth (1988) and are portrayed as a conceptual model, referred to in this report as the Driver Factor Model. Applying weights to the factors appearing in this model in effect changed it into a algorithmic model. The weights were based on an analysis which examined the predictive validity of the factors to actual maintenance performance. This work is also discussed in Evans, Kapp, and Roth (1990), as well as within this report.

The second goal of Phase 2 was to develop a trade-off tool based on the results of the performance analyses. This tool was to be easy-to-use and would allow the assessment of the impact of MPT factors upon maintenance performance.

Phase 3 has four major goals: (1) describe the effort, (2) present the findings of the first two phases, (3) explicate the relationship of this project to ARI's HARDMAN III effort, and (4) indicate lessons learned through the performance of this effort. The remainder of this report focuses on these areas.

It should be pointed out that the underpinnings of this effort rest on data we gathered from various sources, as described later in this report. During our collection procedures and analyses, we discovered that the data available to us were incomplete, not comparable across systems, and imperfect pictures of the ways in which maintenance is performed. We must point out that we searched for the best data sources possible, and ended up with data that are not really appropriate for the types of analyses we undertook. However, these data, and no others, are the only ones available for most MANPRINT efforts. We feel that the methods we used were viable and appropriate, given our project goals, as will be discussed in the next section, but our findings may be suspect due to the nature of the information on which they were employed. Our difficulties with the data are more fully described in the Lessons Learned section of this report.

(Please note, most of the tabular information associated with our discussion of Phase 2 appears in Appendix E. There are four summary tables concerning Phase 2 included with the text. We separated the other tables from the text because of the large number of items.)

PROJECT DESCRIPTION

Phase 1

Purpose

The major purpose of Phase 1 was to generate a logical structure within which to place maintenance-related MANPRINT factors found in existing models. This structure could then be used as a way to identify continuities and discontinuities among the models and to supply a common language or framework in which to understand the models in relation to each other and the system acquisition process.

The models that were the focus of this study were seven sets of models which have been developed by the HARDMAN III project and the Evans and Roth Driver Factor Model. The models are listed and briefly described below:

1. HARDMAN III models (note: Each HARDMAN III tool, except for MANCAP 2, is comprised of two models representing system states, one input model representing an old or predecessor system and a second output model depicting a new or target system, and a process model consisting of the algorithms which manipulate the predecessor state model to produce the output state model.)

   a. System Performance Requirements Estimation Aid (SPARC) (Dahl, et al., 1987) - SPARC is a network model-based tool which is to aid an analyst during the early phases of system acquisition to determine the functional and task performance requirements necessary for a particular material system to attain minimally acceptable performance with regard to its mission.

   b. Manpower Constraints Estimation Aid (M-CON) (O'Brien, 1987a) - M-CON is a Markov chain model-based tool which is to aid an analyst in determining manpower constraints for a material system during the early phases of system acquisition.

   c. Personnel Constraints Estimation Aid (P-CON) (O'Brien, 1987b) - P-CON is a Markov chain model-based tool which is to aid an analyst in determining personnel constraints for a material system during the early phases of system acquisition.

   d. Training Characteristics Estimation Aid (T-CON) (Roth, et al., 1987) - T-CON is a database management model-based tool which is to aid an analyst in determining training likely to be available for Military Occupation Specialties (MOSs) associated with a material system during the early phases of system acquisition.

e. Manpower Determination Aid (MAN-SEVAL) (Archer, et al., 1987) - MAN-SEVAL is a network model-based tool which is to aid an analyst in evaluating manpower requirements entailed by a specific design for a material system.

f. Personnel Requirements Estimation Aid (PERS-EVAL) (O'Brien & Dahl, 1987) - PERS-EVAL is a network model-based tool which is to aid an analyst in evaluating personnel requirements entailed by a specific design for a material system.

g. MANCAP 2 (Dynamics Research Corporation and Micro Analysis and Design, 1989) - MANCAP 2 is a model-based tool which utilizes a combat model scenario in conjunction with a maintenance and operations model to estimate the maintenance repair times, manpower, and supply requirements entailed by a system's mission and maintenance concept and strategy. It is comprised of four state models and one process model. The state models are: (1) an input model of the maintenance function of the comparison system; (2) a model of the maintenance function of the target system (this can be either input or an intermediate model developed by the tool); (3) an input combat battle model; and (4) an output model of maintenance requirements with regard to time to repair, personnel, manpower, and support. The process model represents the algorithms necessary to move from the input models to the output model.

Four of the HARDMAN III tools (SPARC, T-CON, M-CON, and P-CON) are to be used during early phases of system acquisition. The other three tools (MAN-SEVAL, PERS-EVAL, and MANCAP 2) are for use during later stages of system acquisition when there is a system design to evaluate.

2. Driver Factor Model (Evans & Roth, 1988) - The Driver Factor Model is a conceptual model depicting the relationships among requirements and acquisition documents, their contents, and other sources of information used during system acquisition to estimate maintenance burden and to make decisions resulting from the identified burden. This model is a state model.

These eight models, or sets of models in the case of each HARDMAN III tool, were selected because they represent on-going efforts by ARI in the area of MANPRINT related to maintenance. It was felt that whatever structure was developed based on these eight models could be extended to other related modeling efforts as they develop. In addition, the identification of relationships among the models, and among the factors comprising the models, and the structuring of these relationships could serve as an integrating mechanism for the efforts and could be used as a common language or view with which to examine the models and factors for their coverage of maintenance issues. This structure could also serve as a basis for the development of a method for the

early assessment of MPT implications of maintenance requirements in system development.

Method

In Phase 1, factors were identified, classified, organized, and selected for further study. First, the existing documentation for the eight models was reviewed to identify the factors appearing in each model. This step entailed examining the following documents:

1. Concept documents for the HARDMAN III tools:

    a. SPARC (Dahl, et al., 1987)

    b. M-CON (O'Brien, 1987a)

    c. P-CON (O'Brien, 1987b)

    d. T-CON (Roth, et al., 1987)

    e. MAN-SEVAL (Archer, et al., 1987)

    f. PERS-EVAL (O'Brien & Dahl, 1987)

2. Briefing materials on MANCAP 2 - (Dynamics Research Corporation & Micro Analysis and Design, 1989).

3. HARDMAN III CALS MPT2 Data Element Dictionary (O'Brien, 1989).

4. Technical paper describing the Factor Driver Model (Evans & Roth, 1988).

Discussions were also conducted with the ARI project managers of the HARDMAN III effort to expand and clarify the information found in the reviewed documents.

As factors were identified, they were placed into a database using a commercially available database management system (DBMS). Information concerning the model contributing the factor, values the factor could take on (if indicated by the documentation), and source of the value (user, data library, or internal processing) were recorded for each factor.

Once the factor database was completed, the factors were examined to identify multiple occurrences. Multiple-occurring factors were removed so that one occurrence of the factor, only, remained in the database. Additionally, each factor was annotated with a list of all models in which it appeared.

After the factors were reduced to a unique set of items, they were examined with intention of: (1) identifying factors that pertained to similar issues and level of detail of information implied by the factor; and (2) determining if there was any meaningful structure that could be imposed upon

the factors. This review led to the realization that the factors relating to the HARDMAN III models could be subsumed or grouped by the Driver Factor Model factors due to content similarities and differences in levels of implied informational detail among the factors appearing in the models. Therefore the factors from the models were placed in a two-level hierarchy in which some (but not all) factors from the Driver Factor Model comprised the higher, more general, level and the HARDMAN III factors made up sub-factors or elements in the lower, or more detailed, level of the hierarchy.

Since one of the overall goals of the project was to develop weights for a subset of factors from the Driver Factor Model, a second task performed during this phase of the project was the selection of factors for further study. The procedure and outcome for this second task is described in detail later in this report.

Analysis of Factors

Phase 1 resulted in the selection of factors for further study.

Types of Factors

Each of the models has their own unique set of properties with regard to the types of factors appearing in them. Each model is addressed separately in the following paragraphs.

Driver Factor Model. The Driver Factor Model is a conceptual representation of the constraining system and MPT factors that impact the derivation of maintenance burden during system acquisition and the subsequently defined MPT requirements for the system. The model was initially designed to be used as a way to view the process as a whole, rather than to be used explicitly as a means for examining the results of various system, maintenance, or MPT scenarios as they impact maintenance burden. Because of its conceptual nature and designated purpose, the factors found in the Driver Factor Model are of a rather general nature and are difficult to connect to specific measurable types of data.

The Driver Factor Model is a state model representing: (1) the informational sources and types of information used in decision making; and (2) the relationship of factors with regard to interactive influence. However, as a conceptual model, it lacks a process model component which takes an input state and modifies it to produce an output state.

The factors that appear in the Driver Factor Model are of three types. The first class of factor found within this model consists of names of planning and requirements documents, such as the Basis of Issue Plan (BOIP), used during system acquisition.

The second category of factor contains informational elements that can be found in the planning and requirements documents used during system

acquisition. This type of factor includes items such as Operational and Organizational (O & O) concept (an element of many documents, including the O & O Plan).

The final division of factors found in this model includes elements that impact decision making concerning maintenance, during the system acquisition process, but do not necessarily appear within any formal planning or requirements documents. Appendix D lists all the factors from the Driver Factor Model and an indicator of the factor type from the three described above. Figure 1 (fold-out at rear of the report) displays the relationships between factors in the Driver Factor Model as described in Evans and Roth (1988).

Given the nature and purpose of the Driver Factor Model, it is not surprising that the factors that appear within the model are tied closely to the planning and requirements documents, and their content concerning maintenance, used during the acquisition of a system.

<u>HARDMAN III Models</u>. The HARDMAN III tools are comprised of algorithmic models, which are similar with regard to the level of detail of the included factors. Thus these models will be discussed as a group rather than separately. As tools comprised of algorithmic models, all of the HARDMAN III tools rely on the use of algorithms to estimate the system, manpower, personnel, and training constraints for a target system or to evaluate a contractor's system design based on a predecessor system.

Since the HARDMAN III tools generate estimates or evaluations of MPT and system factors for a target system based on a predecessor system, the factors appearing in the tools are at a level of specificity such that system and MPT data for predecessor systems can be extracted from sources such as Manpower Requirements Criteria (MARC) analyses, the Sample Data Collection (SDC) database, and the U. S. Army Personnel Integration Command (USAPIC). These data are then manipulated to produce estimations of MPT and system constraints or evaluate a specific design for a target system.

The fact that HARDMAN III tools are to be used to estimate or evaluate a target system's constraints based on a predecessor system means that each tool (except for MANCAP 2) supports two system or state models: (1) a model of the predecessor system which serves as input; and (2) an output model of the estimated or evaluated target system. Thus for each HARDMAN III tool, there are pairs of factors, one for the predecessor system and one for the target system (the one for which constraints are being developed or which is being evaluated). For example, in P-CON there is a "verbal ability" factor for both the predecessor system and the target system. It should be noted that there is not necessarily a one-to-one correspondence between each factor represented by the predecessor system and the target system. This lack of correspondence is due to the presence of computed factors and values. This is especially apparent in the case of the target system model. In other words, factors that are expressed in the predecessor model are combined internally, processed, and then expressed as a new, unique factor (with a value) for the target system.

In addition to the factors representing the predecessor and target systems, each HARDMAN III tool also supports a process model containing algorithms that generate the estimated or evaluated target system model's

factor values based on the predecessor system model. The process model contains process factors inherent in the algorithms necessary to perform the comparability analysis. These process factors need not be addressed here, because they are not comparable to factors from the Driver Factor Model.

Of the HARDMAN III products, the MANCAP 2 tool contains the most extensive set of process and state models. MANCAP 2 can use five models related to system maintenance, four state models and one process. The state models are: (1) an input model of the maintenance function of the predecessor system; (2) a model of the maintenance function of the target system (this can be either input or an intermediate model developed by the tool); (3) an input combat battle model; and (4) an output model of maintenance requirements with regard to time to repair, personnel, manpower, and support. The process model represents the algorithms necessary to move from the input models to the output model.

Given the types of models utilized by MANCAP 2, the factors that appear within the models are at a level of detail to be supported by data from SDC and other sources of quantitative system, manpower, personnel, and support data. Other factors appearing in MANCAP 2 are specific to the combat model it utilizes, and are not specifically maintenance-related in the same sense as the other models examined during this analysis. These combat model factors will not be further addressed within this report.

Commonalities Among Models

All the models are similar in terms of their general focus. They even overlap with regard to factors contained within them. Appendix C is a list of unique factors extracted from the HARDMAN III state models (less factors implied by the process models, such as "comparison system" and "length of battle" and battle scenario factors). Each factor is notated with an indicator of the models in which it appears and the data source(s) in which it appears (except in the case of overlaps with the Driver Factor Model, in which case the factor is classified by the Driver Factor Model).

As one can see from examining the factor list in Appendix C, there is an extensive overlap between P-CON and PERS-EVAL, and between M-CON and MAN-SEVAL. These congruencies are not surprising, given that P-CON and PERS-EVAL both focus on personnel factors, and the M-CON and MAN-SEVAL focus is manpower. PERS-EVAL also includes many of the factors found in T-CON. MAN-SEVAL overlaps with MANCAP 2, but this is due to the fact that part of the output from MAN-SEVAL serves as a direct input into MANCAP 2. Additionally, several factors from PERS-EVAL and SPARC occur in MANCAP 2. The HARDMAN III and MANCAP 2 models all also overlap with the Driver Factors Model extensively, but in a way very different from the conjunction between each other. (This will be described in more detail later.) However, more important than the point that the models overlap on one or more factors is the fact that certain factors from across all the models can be grouped together into fairly distinct categories, and in most cases all models have one or more factors which appear in each category.

Disjunctions Among Models

The Driver Factor Model was described earlier as "a conceptual representation of the constraining system and MPT issues that impact the derivation of maintenance burden during system acquisition and the subsequently defined MPT requirements for the system." In contrast, the HARDMAN III tools contain algorithmic models which represent actual methods by which MPT and system decisions can be made. This difference in type of model leads to a major disjunction between the HARDMAN III models on one hand, and the Driver Factors Model, on the other.

This disjunction is most obvious in the levels of specificity and measurability of the factors involved. The factors from HARDMAN III, for the most part, have definitions which lead them to be supportable with specific data relating to a system, MOS, mission, etc. On the other hand, the factors that appear in the Driver Factor Model are more general and represent the state of the maintenance burden determination process as a whole.

An additional difference between the HARDMAN III models and the Driver Factors model (resulting from the conceptual versus algorithmic model distinction) is the presence or absence of a process model and input and output state model components. The HARDMAN III models all include algorithmically-based process models which transform one or more input state models into an output state model, whereas the Driver Factor Model does not. This difference results in the lack of algorithmic factors and paired input and output factors for the Driver Factor Model and the presence of such factors in the other models. The goal of Phase 2 of the current effort was to convert the Driver Factor Model from a conceptual model into an algorithmic one, with paired input and output states and set of processing algorithms.

Within the HARDMAN III tools there are three disjunctions. First, four of the tools are designed for aiding in decision-making early in system acquisition prior to the development of a system design. In fact, these tools may be used by an analyst to help develop a system specification. The tools for early use are SPARC, M-CON, P-CON, and T-CON. The other three tools, MAN-SEVAL, PERS-EVAL, and MANCAP 2 are meant for use during later stages of system acquisition, when there is a design to be evaluated.

A second difference exists between the models comprising the HARDMAN III tools. Two of the tools, M-CON and P-CON, use a Markov chain process model, whereas SPARC, MAN-SEVAL, PERS-EVAL, and MANCAP 2 are supported by network process models. T-CON, on the other hand, primarily uses data base retrieval and sorting algorithms.

A final major disjunction occurs in the case of the HARDMAN III tool SPARC. Of the HARDMAN III tools, SPARC overlaps least with any of the other models reviewed for this project. This disjunction between SPARC and the other models results from the SPARC's system-oriented focus, rather than a MPT direction. However, the results from SPARC are used for making decisions concerning the values for some of the parameters for the other models.

Selection of Candidate Factors

When the models and factors were examined, it was discovered that there was a clear hierarchical relationship between the factors in the HARDMAN III models and many of the factors within the Driver Factor Model. Many of the factors in the Driver Factor Model could be classified as general factors (metafactors) which could be more fully described by sets of factors from the HARDMAN III models. For example, the Driver Factor Model factor "availability" could be described by combining the following factors found in P-CON: (1) attrition, (2) migration from MOS, (3) promotion rates, and (4) retention, with the factors "current authorizations" and "current operating strength" from M-CON. Thus, one can consider the factors from the HARDMAN III models to be elemental factors that can be used to describe or define their associated metafactors which can be found within the Driver Factor Model. The classification of HARDMAN III factors by the Driver Factors Model factors to which they pertain appears in Appendix C. This classification resulted in 39 groups of metafactors which could be described by elemental factors. These 39 categories of metafactors appear in Table 1.

Examination, however, revealed that the factors in the Driver Factor Model are not orthogonal. In other words, many elemental factors which can be used to describe one metafactor frequently can be assigned to one or more other metafactors. This can be seen clearly in some of the listings in Appendix C and Table 1. There are also some factors from the Driver Factor Model which are elemental in the same way as factors from the other models are. These factors from the Driver Factor Model can be seen as operating as both metafactors and elemental factors, and they often appear in models other than the Driver Factor Model (e.g., the factor "number of systems" or "eaches" appears in both MANCAP 2 and the Driver Factor Model).

All of the HARDMAN III state model factors which are not specific to either the predecessor system or battle simulation processes can be assigned to a Driver Factor Model factor. Even all the factors related to SPARC could be so classified. However, there are several factors from the Driver Factor Model which cannot be described in terms of any of the factors found in the other models. These are shown in Table 2.

Elemental factors that are appropriate for algorithmic processing and can describe the metafactors shown in Table 2 need to be identified in order to ensure the development of tools which address all aspects of the relationships among system, MPT, maintenance burden, and support for maintenance performance.

To briefly summarize, each HARDMAN III factor can be used to describe one or more Driver Factor Model factors. However, there is a subset of Driver Factor Model factors which cannot be described using HARDMAN III factors. There are also some Driver Factor Model factors which are at the same level of detail as the HARDMAN III factors and therefore can serve as either elemental factors to describe other Driver Factor Model factors or metafactors.

The identified hierarchial relationship among the Driver Factor Model factors and the HARDMAN III factors allows one to view the Driver Factor Model

as a potential organizer and framework for relating the outputs from the other models to one another. For example, take again the Driver Factor of "availability" which has elemental factors from both P-CON and M-CON. In order to come to an understanding about "availability" for a particular situation, one would have to exercise both M-CON and P-CON for that situation. (One caution must be made, however. Although the elemental factors have been identified as components for the description of the metafactors, one should not be led to think that the identified elemental factors for a particular metafactor (or metafactor group) are the only factors describing the metafactor. In fact, for each metafactor for which elemental factors have been identified, there are probably many other actual elemental factors which have been not identified since they are not used in the models examined for this effort.)

In addition to describing metafactors from the Driver Factor Model, the Hardman III factors can be used to convert the Driver Factor Model from a conceptual model to an algorithmic one. HARDMAN III factors can be used to describe Driver Factor Model factors and are at a level of detail for which data are available for the description of input and output models.

Table 1. Thirty-nine Metafactor Categories for Elemental Factors

Availability

BOIP, MOSs, Existing MOS Data, Organizational Structure

BOIP, Summative Manpower Requirements, Manpower, TTHS Factors Data

BOIP, Summative Manpower Requirements, Number of People in Manpower Pool, Availability

BOIP, System, Number of Systems, Eaches

BOIP, TOE, Number of Systems per Unit

Levels of Maintenance, O & O Concept,

Maintenance Concept, Organizational Concepts

LSA, Task

LSA, MAC, System Maintenance Characteristics, Task, Service and Repair Tasks, Fault Isolation Tasks, Maintenance Tasks, Task Performance Requirements (TPR)

LSA, MAC, System Maintenance Characteristics, Maintenance Burden, MOSs, Maintenance Profile, Task Allocation Strategy, Task Performance Requirements (TPR), Tasks and Levels

LSA, Maintenance Burden, MAC, Organizational Concepts, LSA, System Performance Requirements & Constraints, System Maintenance Characteristics, Task Performance Requirements (TPR)

LSA, System

LSA, Task, Service and Repair Tasks, Fault Isolation

Tasks, Maintenance Tasks

Maintenance Burden, BOIP, MAC, Maintenance Allocation

Maintenance Strategy, Task Allocation Strategy

Maintenance Tasks, Maintenance Burden

Manpower Pool Characteristics, Aptitude, Personnel to be Trained, Entry Level Characteristics

Table 1. Thirty-nine Metafactor Categories for Elemental Factors (Cont.)

Material & support System; Provisioning; Spares; POL, AMMO, etc.

O & O Concept

O & O Concept, BOIP, Organizational Structure

O & O Concept, LSA

O & O Concept, Maintenance Concept

O & O Concept, OPTEMPO

O & O Concept, OPTEMPO, Use Rates, Maintenance Burden

O & O Concept, System Performance Requirements & Constraints, System Design, ROC

System Performance Requirements & Constraints, OPTEMPO, ROC

System Performance Requirements & Constraints

System Performance Requirements & Constraints, LSA, System Maintenance Characteristics

System Performance Requirements & Constraints, System Maintenance Characteristics, LSA

QQPRI, KSAs, Personnel Requirements

QQPRI, System Performance Requirements & Constraints

QQPRI, Personnel Requirements

QQPRI, Task Performance Requirements (TPR)

QQPRI, Training Devices

QQPRI, Training Requirements

Summative Manpower, BOIP, Level of Maintenance

Task

Training Device, Training Subsystem

Training Requirements, Training Subsystem

Table 2. Metafactors without Elemental Factors

TMDE capabilities
Testability initiatives
Failure modes analysis
Accessibility design initiatives
Documentation
TMDE
BIT/BITE capability
Technological opportunities
BIT/BITE use
Failure modes and components
HFE design initiatives
Maintainability design initiatives

There are two ways in which the Driver Factor Model can be converted from a conceptual model to an algorithmic one. One way for converting the Driver Factor Model to an algorithmic model is to make many algorithmic "micro" models, each representing one metafactor. Each micro model would be comprised of all of the elemental factors identified as descriptive of it. Input and output states for the elemental factors describing the metafactor would be determined, and algorithms appropriate to those states would be developed. These "micro" models would then be combined via algorithmic processes to form a large algorithmic model.

The second method for conversion of the Driver Factor Model is to select (or sample) for each metafactor (or subset of metafactors) one or more elemental factors that describe the metafactor. The elemental factor(s) would be selected based on logical assumptions concerning their predictive validity with regard to maintenance performance. Each elemental factor (or factors) would then be used to be represent the associated metafactor. Input and output states for the elemental factors would be identified. Finally, algorithms would be developed that define the relationships between the input and output states. For this project, these algorithms would include weightings for each input factor. If a single elemental factor has been selected to represent a metafactor, then the weight for the elemental factor would be assumed to also represent the weight for the metafactor. If two or more elemental factors are selected to represent a metafactor, then a single weight for the metafactor would be developed from the weights associated with the elemental factors.

We selected the second method for the conversion of the Driver Factor Model to an algorithmic model. Briefly our rationale was as follows. This project is to result in two outcomes: (1) a structure in which to understand, in at least a qualitative sense, the relationship between the maintenance performance and the factors that affect it as represented by the Driver Factor Model; and (2) a easy-to-use trade-off tool. The trade-off tool is to utilize the structure and relationships derived from the integration of the Driver Factor Model with HARDMAN III models in order to make approximations between the outcome of the manipulation of MPT and system factors upon maintenance.

Since the tool is to be easy to use, it should require the user to input no more information than that needed to support 20 elemental factors representing selected Driver Factor Model metafactors. If we selected the conversion method in which all elemental factors descriptive of metafactors are used, then the user of the tool would have to supply much more information than needed for 20 elemental factors.

To summarize, one can view the factors from the Driver Factors Model as metafactors around which to organize the factors found in the HARDMAN III models. With regard to the types of models examined, the Driver Factors Model is a conceptual model whereas the models from HARDMAN III can be classified as algorithmic models. However, the Driver Factor Model can be described in terms of elemental factors selected from the HARDMAN III, and therefore can be converted into an algorithmic model once the appropriate algorithms have been developed, and input and output state models have been defined.

Although we selected the second method of converting the Driver Factor Model to an algorithmic one, the model, as shown in Figure 1, contains 53 factors. Fifty-three metafactors are too many to include in a simple-to-use tool. If we use the metafactor groups in Table 1, we reduce this number to 39 metafactor "groups" for which elemental factors have been identified. Since we will be identifying elemental factors to represent metafactors, we needed to consider the metafactor groups listed in Table 1 as a primary source from which to select. We also considered the 12 metafactors, listed in Table 2, for which no elemental factors have been identified. However, 39 metafactor groups plus 12 metafactors equal 51 metafactors and metafactor groups to examine.

Fifty-one metafactors or groups are still excessive for inclusion in the tool. This means we require a strategy for reducing the number of metafactors to include in our algorithmic model. One potential means for reducing the numbers of metafactors is to omit some of the metafactors which we have not identified descriptive elemental factors. Those we have elected to omit have to do with system design issues, since these are difficult to specify at a level of detail appropriate for measurement. Elimination of these types of metafactors would leave us with:

1. Test, Measurement, and Diagnostic Equipment (TMDE) capabilities
2. Documentation
3. TMDE
4. Built-In Test/Build-In Test Equipment (BIT/BITE) capability
5. BIT/BITE use

We can also collapse TMDE/BIT/BITE factors into two more general ones of (1) TMDE/BIT/BITE capabilities, and (2) TMDE/BIT/BITE use. Further reduction of the above list of metafactors can be undertaken by removing metafactors for which it is difficult to identify elemental factors or for which supporting data may be lacking. These factors are:

1. Documentation (to determine the elemental factors of which documentation is comprised would require an effort greater than the present one).
2. TMDE/BIT/BITE use (it is difficult to locate sources that detail proposed TMDE/BIT/BITE use).

If the above metafactors are removed, we are left with TMDE/BIT/BITE capabilities as the remaining metafactor for which elemental factors have not been identified. If we define one or more elemental factors for TMDE/BIT/BITE capabilities, we could include it with the 39 metafactor groups for which there are elemental factors. Possible elemental factors for TMDE/BIT/BITE capabilities are:

1. Number of TMDE/BIT/BITE supports for the system.
2. Complexity of use of the TMDE/BIT/BITE supports.
3. Failure rate of TMDE/BIT/BITE when used.
4. Mean time to find failure using TMDE/BIT/BITE.

Now the list contains 40 metafactor groups (the 39 listed in Table 1 and TMDE/BIT/BITE capabilities). This is still too many. The next step is to identify in our list of metafactors ones comprised of elemental factors most likely to be predictive of actual maintenance performance as reflected in factors such as mean time to repair.

Of these predictive elemental factors, we selected 38 elemental factors that represent 12 metafactors or metafactor groups during Phase 1. These elemental and meta factors appear in Appendix B. These elemental factors (or groups of elemental factors) represent a subset of the 40 metafactor groups. Thirty-eight elemental factors were initially selected, rather than 20 as targeted, for inclusion in the tool to be developed because we assume some of our selected elemental factors will not be predictive of maintenance performance. We revised our list as described in our discussion of Phase 2.

Phase 2

Purpose

Phase 2 of this project had five major goals.

First, a conceptual model of the relationships among Manpower, Personnel, and Training (MPT), system requirements as determined during system acquisition, and maintenance performance was to be converted to an algorithmic model. This model appears in Evans & Roth (1988) and depicts conceptually the driving forces behind decisions and issues considered during acquisition which finally impact estimates of, and actual, maintenance performance. This model is referred throughout this report as the Driver Factor Model. Initial steps toward conversion of the model were taken in Phase 1 of the project (reported in Evans, Roth, & Hogg, 1990). In Phase 1, the Driver Factor Model was defined as a set of metafactors. This was done because the factors appearing in the Driver Model, for the most part, were not at a level amenable to direct observation and measurement. These metafactors were then redefined by sets of elemental factors which were measurable. These elemental factors were drawn from models that comprise HARDMAN III (a set of MANPRINT tools), as described in the concept documents for these tools (Dahl, et al., 1987; O'Brien & Dahl, 1987; Dynamics Research Corporation and Micro Analysis and Design, 1989).

The second objective of Phase 2 was to determine weights for factors, both the elemental factors and the metafactors, appearing in the converted model. These weights would indicate the relative importance of each factor for the performance of maintenance.

The third objective was to assign certainty ratings to these weights as indication of their validity. The plan was to base these certainty ratings on the quality and quantity of data which were used in the determination of each weight.

The fourth aim of this phase was to assign a common metric to factors (both elemental and meta) so that they their weights could be directly compared. In this way, one would be able to identify the importance of one factor as compared to the others.

The final goal of Phase 2 was the building of a trade-off tool based on the structure identified in Phase 1, in conjunction with the weights developed in Phase 2, to be used to estimate impact of MPT factors on maintenance performance. This tool was to use the algorithmic model developed during this phase as its basis. The tool was to interface with tools resulting from other MANPRINT efforts by either supplying the external tools with data or using data generated by these tools.

Method

Selection of Approach

Five potential approaches were examined as to their suitability for generation of factor weights and tool development. They were: (1) meta-analysis, (2) Isoperformance Modeling, (3) simulation, (4) multiple regression, and (5) neural networks. Each is briefly described below.

Meta-Analysis. Meta-analysis is a statistical technique whereby the results from multiple research studies are combined in such a way as to indicate the relationships among the various independent and dependent variables appearing in the separate studies. For example, if one wished to determine the relationship among length of training, personnel aptitude, and manpower requirements as they impact task performance, one would have to find, as a minimum, studies containing the following statistically-described relationships between the independent variables for the dependent variable of task performance: (1) training and aptitude, (2) training and manpower, and (3) manpower and aptitude. The findings from these studies could then be combined to produce the relationship among the three independent variables as they relate to the dependent variable of task performance.

The meta-analytic approach has great potential as a method in cases in which no one study addresses several variables of interest, as in the case of the relationship among MPT and system variables as they pertain to maintenance performance. Meta-analysis would allow us to find the relationships among the factors from the Driver Factor Model and characterize them statistically.

The meta-analytic approach is conceptually feasible for the aims of this project. However, Jones, et al. (1986), using meta-analysis on a similar problem as ours, found the approach unworkable. Jones and his colleagues, under contract to the U.S. Air Force Human Resources Laboratory, examined the relationship among the variables of aptitude, length of training, and system complexity (three of the variables of interest in this project) as they impacted task performance. These researchers examined 10,000 research citations having titles indicating relevance to their endeavour. Of these 10,000 references, only 10 studies contained enough information concerning the statistical methods employed in the study to allow them to be combined using meta-analytic techniques. The results of meta-analysis were inconclusive due to the paucity of data.

Jones, and his colleagues (1986) focused on a subset of the factors in which we are interested in this project and found inconclusive results. It is safe to assume that if we were to replicate their study and also include more factors (thus requiring the identification of more studies depicting relationships among the factors), we would also have inconclusive results. For this reason the meta-analytic approach was rejected.

Isoperformance Modeling. Isoperformance modeling is a trade-off method developed by Jones, et al. (1986), and fully described in Kennedy, et al. (1988), to examine personnel, training, and system factors as they impact task performance. The method consists of modeling the relationship between personnel aptitude levels and length of training necessary to reach a certain level of task proficiency given a set of system parameters. Outputs of the procedure are sets of curves representing the relationships among the variables. The method requires the user to determine his or her population type and to estimate: (1) the distribution of manpower in different aptitude categories; (2) the maximum time necessary to train 5 percent of the personnel to proficiency for each aptitude category; (3) the percent of persons who will be proficient given the maximum allowable training time; (4) the time required for 50 percent of the personnel to be trained to proficiency; and (5) the percent of personnel in different aptitude categories for different system configurations.

The Isoperformance modeling approach was considered as a possibility for the present effort because it focuses directly on factors that appear in the Driver Factor Model. However, this approach has several drawbacks which removed it from consideration as an approach.

First, to use Isoperformance modeling, given the need to use the factors appearing in the Driver Factor Model, the Isoperformance Model would have to be greatly extended to accommodate the other factors appearing in the Driver Factor Model. This could be accomplished one of two ways: (1) by performing the tasks Jones, et al. (1986), undertook to develop the model in the first place, i.e., meta-analysis and specific research; or (2) by employing some other technique, such as multiple regression to determine relationships among the factors appearing in the Isoperformance Model and the others appearing in the Driver Factor Model.

The first option, performing meta-analyses and specific research, was deemed impractical. The reasons for not using a meta-analytic approach are discussed in a previous section. Performing specific research of the type performed by Jones, et al. (1986) which included making mock-ups of systems with differing characteristics, training subjects of varying aptitudes for different lengths of time on system operation, was not feasible given the resources for the present effort. In the case in which model extension is accomplished via multiple regression or some other technique for determining factor relationships, the technique must be performed on both the factors existing in the current Isoperformance Model and the factors to be added to it, so that the relationships between factor sets can be determined. Given the need to perform the technique on all factors, and the fact that the methods for model extension also are appropriate for model development, it seems to make more sense to use the modeling technique by itself, rather than use it and "glue" the findings onto the existing Isoperformance Model.

Second, once an Isoperformance Model is developed, its use, as described by Kennedy, et al. (1988), requires the user to make certain estimates concerning end-points of curves based on the user's experience or research using system mock-ups. For the current Isoperformance Modeling tool, these estimates include decisions about the distribution of personnel aptitudes and length of training required for the upper and lower ends of the distribution, given a particular system configuration. In other words, the user must be an expert in, or have informational resources on, expected personnel aptitudes and training needs. This requirement of expertise or background information limits the utility of the tool by non-expert personnel.

Simulation. Another approach to determining the relationships among factors is to build a process, or simulation, model of system acquisition which outputs expected maintenance requirements for a generic system. Then the model could be tested by supplying it with actual data for each of several systems. The outputs of the model could then be compared to actual maintenance requirements for each system. If the predicted and actual requirements do not match, then the simulation could be modified until its outputs do match the actual maintenance requirements within acceptable limits. This model could then be used to generate maintenance requirements for specific systems, given expected MPT availabilities.

A major strength of the simulation approach is that it can control for, and reflect, the temporal relationships among decisions which define values for the metafactors (as described by elemental factors) in the Driver Factor Model, as they impact the acquisition process as it pertains to maintenance requirements. For example, a simulation could reflect that the information that affects maintenance appearing in the Operational and Organizational Plan directs some of the intermediate decisions made about maintenance requirements.

Simulation of the decision process for maintenance requirements determination is an approach which would algorithmically depict the relationships appearing in the Driver Factor Model, once these metafactors have been defined as elemental factors. However, this method has several implementation difficulties. First of all, it is very difficult to ascertain the specific influences in the cascading relationships among the factors in the Driver Factor Model. The model depicts three types of factors: (1) driver factors which supply the initial impetus; (2) intermediate factors which reflect some, but not necessarily all, of the influence of the driver factors; and (3) the driven factors, such as identified maintenance burden and specific training requirements, which are derived from the intermediate factors, but whose relationship to the driver factors may not be traceable in any direct way. To thoroughly trace all the relationships among factors in the Driver Factor Model and to determine how specific relationships came to be would require a major investigatory effort of the acquisition process as a whole, and of specific systems on which the model is to be based. The present effort did not have the resources to attempt this level of detailed examination.

A second problem with our using the simulation approach for this effort was the project requirement to determine weightings for each factor so their importance can be compared. Although the algorithms comprising the simulation

would have "factor importance" inherent in them, it is not obvious the way in which a process or simulation model could supply factor weightings (or some measure of factor importance) directly. The way in which one could determine factor importance with a simulation is to supply it with cases in which one of the factors is systematically varied, and then compute and compare the differences between the outcomes given different values for the factor being manipulated. From these comparisons, one could determine the relative importance of a factor during acquisition for the system whose data set has been fed into the simulation. Thus one could produce system-specific factor weights. If this process was performed for several systems for the various factors, one could generate some general rules about the importance of different factors. However, this process, could potentially be very resource intensive.

A final difficulty with the simulation approach is that past experience has shown that tools developed using this method are more algorithmically intense during application than some other methods (Roth, 1988). This problem is reflected in the long delays in output generation experienced with using these tools. However, as computer hardware becomes more powerful, this drawback will disappear.

Multiple Regression. The fourth method considered for this effort was the application of multiple regression, a statistical method, for the development of an equation (or set of equations) containing the MPT and system elemental factors which represented the Driver Factor Model metafactors. Multiple regression, as a method, generates an equation containing a dependent variable that is predicted by one or more weighted factors plus a constant value. This equation is derived from a data set containing historical values for the factors and the dependent variable. The predictiveness of the equation is reflected in the amount of variance in the dependent variable accounted for by the factors in the equation. Multiple regression can generate either a linear equation or a non-linear one. In most research, the linear option is selected or data are transformed such that a linear equation is the best fit for the data.

Multiple regression was examined as a possible approach for several reasons. First of all, the equation that results from the method reflects the data used in its development, as well as the relationships among the factors of interest. The method also produces factor weights as part of the equation. These factor weights come in two forms: (1) the weight for the factor given the unstandardized data set used in the analysis; and (2) a weight based on the conversion of the data to standardized scores (Z-scores). Weights of the latter type can be compared to each other, with the higher the value of the weight being indicative of the relative importance of the factor. Second, the equation produced by multiple regression could easily be used as the basis for a tool to predict maintenance performance, given a set of values for the factors included in the equation.

Multiple regression requires much of the same data for its support as one would use to refine a simulation model. However, multiple regression is not as resource intensive as simulation because: (1) multiple regression analyses can be performed using readily available software statistical packages which run quickly on an IBM PC or compatible, rather than requiring the time

necessary to develop and implement the algorithms specific to model; and (2) multiple regression produces factor weights as part of its equation, rather than requiring multiple simulation runs and comparisons of the outputs from those runs.

There are drawbacks to multiple regression, however. First, one uses multiple regression to find strong, predictive relationships, in which the independent factors account for most of the variance associated with the dependent variable. If the independent factors account for a majority of the dependent variable variance, then one can assume that the predictive value of the equation is relatively high. However, if the independent factors do not account for much of the dependent variable variance, then those independent factors are not good predictors of the dependent variable, and any tool based on such an equation would lead to doubtful results, at best. Finally, a model based on a multiple regression equation cannot account for factor impacts associated with the temporal order of events (such as intermediate results), in the way a simulation can.

Neural Network. The application of neural networking concepts was the final method we explored for use on this effort. Neural networking is a set of concepts that use a biological model based on the workings of the neuronal system. Neurons are biological elements which can be either turned on or off, given the occurrence of an event. Neurons exist in layers in which the results of stimulation of the lower layer either turn on or off the neurons in the next higher layer, until the final layer is reached. All of this processing through layers results in the coalescing of many initial, local stimuli into a coherent and interpreted whole. Such neuronal systems are capable of learning through experience, generalizing, and filling in missing information.

In the past few years, many researchers have examined the way in which neuronal systems work and have developed algorithms to simulate such systems (Rummelhart & McClelland, 1986). Most of the work in this area has focused on producing simulations which mimic human cognitive behavior; however, many of the concepts and algorithms associated with these simulations also have been seen as ways to approach a diverse set of non-biological problems. Some of these areas include handwriting identification (Newquist, 1990) and analysis of business financial health (Barker, 1990). The common thread among all the areas in which neural network concepts have been applied is the ability of the developed network to match new or partial patterns with old ones and generate outcome predictions or fill in missing data.

The input to neural network algorithms is a data set comprised of initial inputs (for the bottom layer of neurons) and final outputs. (These can be thought of as the independent factor and dependent variable values, respectively.) Some other constraints are set up such as the number of intermediate layers and the number of neurons (or points at which data are combined) for each layer. The data set is run through the algorithms until a certain constraint value is reached. (The specific constraint and value selected are determined by the specific set of algorithms used and the application.) At this point, the network has finished "learning" the data set and can be tested by supplying it with new values for each of the neurons in the bottom layer and comparing the network's predicted outcome with the actual outcome. If the predicted outcome and actual outcome are the same, then the network has

"learned" correctly. If not, the network may require more training trials, better data, or different algorithms to generate it. After the learning process has been completed, each neuron in the network has a weighting associated with it.

The bottom layer of neurons can be thought of as factors with data values. The algorithms convert the inputs into values ranging from -1 to +1 and input these values into the next level of neurons/factors. All input values are sent to each neuron/factor at the second level and combined and converted into new values for input into the next level. This process continues until the output layer is reached. It must be pointed out that the algorithms used to simulate the learning capabilities of neural networks are identical to iterative non-linear multiple regression (White, 1989).

Neural networks were investigated as a possible approach because of the claim of some researchers of greater predictive accuracy for neural networks than for linear multiple regression (Kohonen, et al., 1988), although this claim for neural network modeling superiority in all prediction cases has recently been disputed (Weiss & Kapouleas, 1989). The supposed difference in accuracy results from: (1) an assumption that most factors in reality are associated via non-linear or non-additive relationships rather than linear and/or additive ones; and (2) the iterative aspect of neural network training is comparable to feeding in many duplicate cases, thus increasing the degrees of freedom used to calculate the variance between cases and decreasing the variance between cases. Neural networking methods also result in weights for factors which could be used to gauge the importance of the various factors. Finally, network models can be used for "filling in" missing data, which is useful for a trade-off tool.

With regard to the feasibility of using neural network methods for this effort, it offered promise. For its use, we would have to gather the same data as we would for multiple regression or for simulation refinement. However, implementation of neural network methods is more resource intensive than multiple regression due to the need to: (1) make multiple training runs, and (2) manipulate the algorithmic constraints until a satisfactory network has been developed.

Selected Approach

After examination of the approaches described in the above paragraphs, we determined that linear multiple regression would be the most appropriate technique for this project given: (1) the project requirements for factor weights and algorithms to be imbedded in a spreadsheet format; and (2) the resources available to the project. We rejected the other approaches for the following reasons:

1. Meta-analysis was rejected because of the dismaying results in its application to almost identical factors by Jones, et. al. (1986).

2. Isoperformance modeling was rejected because to expand the current model in such a way as to address all the factors in the Driver Factor Model, we would have to perform multiple regression, or some

other technique to identify factor relationships, on all of the factors of interest and embed the results in the model. Another difficulty we saw with the product associated with this model was its extensive need for input by persons with expertise in the details of interactions of training, personnel, and system design.

3. With regard to a simulation approach, the approach would require the same data collection process as multiple regression. However, the post-data collection process would be much more resource intensive than multiple regression, and more intensive than what the project could support. It is also questionable if the product of the simulation approach would result in an outcome that could directly address the project goals to the same level as multiple regression.

4. We selected the neural network approach as a back-up approach to apply in the event resources were available after the application of multiple regression. The neural network methods are more resource intensive than multiple regression, but potentially could result in a more accurate model. However, since the claim for improved accuracy with neural network models is currently in dispute, we felt that we should select the more conservative and well-understood linear multiple regression approach.

After we had rejected the other examined modeling methods, we determined that the linear multiple regression equations we would develop would include the elemental factors identified during Phase 1 (Evans, Roth, & Hogg, 1990) which represent metafactors found in the Driver Factor Model. These elemental factors, or some subset of them, would serve as our independent factors. These elemental factors, singly and in combination, would represent a subset of the metafactors identified in Phase 1. The factors we finally selected appear in Table 1 of Appendix E.

The elemental factors which were selected in Phase 1 were examined prior to their inclusion in the multiple regression analysis. This step was done to determine if any of the factors should be dropped or modified due to a paucity of quantifiable data. In general, this process resulted in the removal of many factors related to the system design and potential ease of maintenance. For example, we found very little documented and measurable data on the amount and quality of Built In Test/Built In Test Equipment (BIT/BITE) expected for the systems for which we had data. However, we made sure to include factors which previous research suggested as important (and for which we had quantifiable data), such as personnel aptitude and training, as used by Kennedy and his colleagues in their work with Isoperformance Modeling.

This examination process resulted in the selection of a total of 24 independent elemental factors from the 38 elemental factors selected in Phase 1. Five of these factors were categorical, so they were re-coded as sets of dummy variables, with each dummy variable having a value of either 0 or 1, depending on the value for the categorical factor. For example, if the value for system type (SYS_TYPE) was 2, then a factor called SYS2 was created such that for all cases in which SYS_TYPE equaled 2, the value of SYS2 would be 1. In all other cases the value of SYS2 would be 0. The complete set of independent factors, including the dummy variables, appears in Table 1 of Appendix E.

The table contains the factor name as it appears in the multiple regression analysis, its definition, and the metafactor which it represents.

We selected several dependent measures to investigate. All of these measures are indices of actual maintenance performance. Our dependent measures were: (1) actual mean time to test; (2) actual mean time to inspect; (3) actual mean time to replace a component; (4) actual mean time to remove or install a component; (5) actual mean time to repair; (6) actual time to service the system; (7) actual time to overhaul; and (8) actual maintenance manhours expended per year by personnel of a particular type of Military Occupational Specialty (MOS). These dependent measures are shown in Table 2 of Appendix E.

We decided to focus on the time to perform maintenance because the Army's final goal with this type of effort is to have some way to better predict actual maintenance requirements, given certain plans for maintenance that are being made. During the acquisition process, estimates are made as to the mean time it will take personnel of MOSs associated with the system to perform various maintenance tasks. If we confined our investigation to developing an equation to predict planned maintenance performance which is based on earlier factors (e.g., expected operational tempo (OPTEMPO), expected mission duration, mission, personnel qualifications, expected manpower, etc.), there was no guarantee that the maintenance performance plans would reflect actual maintenance performance. Therefore, we determined that planned maintenance performance, as well as other elemental factors reflecting Driver Model Factors should be examined for their predictive capability with regard to actual maintenance performance.

We felt that if relationships do exist among planning factors and actual maintenance, then the resulting multiple regression equations could be used as the basis for a trade-off tool. If no strong predictive relationships could be discovered, it would indicate that there is a major problem with feeding actual maintenance data collected in the field back into the planning process for subsequent models of a system.

Another potential dependent measure we considered was system operational availability (A_o). Operational availability is a measure which takes into account time to perfrom maintenance and administrative tasks, as well as actual times in which the system is operating or is operational, but standing by. This measure combines the effects of factors inherent in the system design (such as BIT/BITE capability or environmental constraints), as reflected by the operating, stand-by, and maintenance times, with the effects of MPT factors reflected in the maintenance and administrative times. The formula for Ao can be found in TRADOC/DARCOM PAM 70-11 (1985) as follows:

$$A_o = \frac{OT + ST}{OT + ST + TCM + TPM + TALDT}$$

where:

OT - Operating time during a given calendar time period

ST - Standby time (not operating but assumed operable)

TCM - Total corrective maintenance downtime in clock hours during the given time period

TPM - Total preventative maintenance downtime in clockhours during the stated OT period

TALDT - Total administrative and logistics downtime spent waiting for parts, maintenance personnel, or transportation per given calendar time period

We had initially intended to use A_o as dependent measure. However, two project developments occurred which changed our decision. First, through discussions with ARI personnel involved with HARDMAN III, we determined that A_o might be too gross of a measure for the factors with which we were concerned, and was likely to be more related to the system factors than to MPT factors. (Please note, that during factor selection, we removed many of the system factors from consideration due to lack of available information concerning them.) It was also mentioned during our discussion that the capability to predict task times for the types of tasks appearing in Maintenance Allocation Charts (MACs) would be more useful as input to the HARDMAN III tools than A_o would be.

Second, although Lowry and Seaver (1988) have developed a method for collecting availability data at the level of detail appropriate for use in MANPRINT analyses, their method requires the researcher to measure maintenance performance times for tasks which do not directly map on to MAC tasks. For example, this method requires separate time measurements for preparation, item obtainment, checkout, fault isolation, fault correction, and cleanup, rather than lumping all of these times under "repair" as occurs in MACs and as collected by several commodity commands for their SDC data bases.

It is likely that the measurements required by the Lowry and Seaver method result in a very good measure of A_o (or as they refer to it, $A_{MANPRINT}$). However, we were constrained by our resources to the type of dependent measure data we could collect, both with regard to performance times and estimates of Ao. We could only gather data previously recorded by the Army. This constraint meant that we had no control over the types of maintenance performance times available to calculate Ao. We also had no control over the types of times used by the commodity commands in their own calculations of A_o.

Furthermore, as we examined our collected SDC data, we determined that we did not have information from all of our SDC sources as to how they calculated

other component elements of the availability equation, in addition to maintenance times. For example, the "given calendar time period" is a value which can be arbitrarily selected. It is conceivable that this value differs for each of our target systems. We could assume that the calendar time period was one year in all cases, but the documentation concerning the SDC systems supplied to us by MRSA indicated that "calendar time period" was an arbitrary value established for the specific system under investigation. And, in deed, our examination of SDC-generated reports for Tank-Automotive Command (TACOM) and Armament, Munitions, and Chemical Command (AMCCOM) systems indicated that A_o was often based on different numbers of system hours depending on the system. Therefore we felt that there was a possibility for bias if we had A_o values for systems based on wide ranges of calendar time periods. This was another reason why we decided not to use A_o as a dependent measure.

It should be noted that although we selected factors reflecting a system's maintenance concept, we did not include any that represent the system maintenance strategy. The reason for this exclusion was that almost none of the planning documents we examined included any statements such as "fix forward concept will be applied with contact team use" which could be interpreted as reflecting a maintenance strategy. It appears from our examination of documents, that numbers and types of levels of maintenance are spelled out, but the actual strategy employed to allocate tasks, make decisions concerning interaction between maintenance level, etc. are set by Army policy across systems and may fluctuate several times over the life cycle of the fielded system.

One major concern we had with our selected method was its requirement for historical data reflecting the factors under examination. If data are not available or inconsistent, it would mean that we would be required to make many assumptions and generalizations about the data which might limit the generalizability of the developed multiple regression equations. We felt the difficulties that might be associated with the data potentially would be minimal, given that the U. S. Army has requirements, standards, and procedures for the development of types of documents and sources from which we were going to gather data.

Data

Data were identified and collected for nine systems. Our original goal was to gather data for twenty systems. These systems were selected because of their use in other MANPRINT efforts. However, we found that actual maintenance data were available for only fifteen of these systems. This number was further reduced by the lack of planning documents for some of the systems and the current unavailability of actual maintenance performance data by personnel for several systems.

Selected systems. The systems for which we were able to acquire both planning documents and maintenance performance data are as shown in Table 3 of Appendix E. Table 3 presents the system designator and its system type.

Data for independent variables. The data for the independent factors came from many sources. These sources included:

1. Required Operational Capabilities documents (ROCs) delineating system performance requirements;

2. Basis Of Issue Plans (BOIPs) which indicate the number of systems and personnel types to be fielded to each type of receiving unit, as well as a statement of system mission;

3. FOOTPRINT reports which contain personnel characteristics for specific MOSs;

4. CROSSWALK reports which list the MOSs associated with a specific system;

5. Logistics Support Analysis Record (LSAR) task data in which expected maintenance tasks are allocated to the MOSs and maintenance levels by component and task type, and assigned expected times;

6. Maintenance Allocation Charts (MACs) which are derived from the LSAR task data and indicate for a system component: the task to be performed, the time required to perform the task, and the maintenance level at which it will be performed;

7. Material Fielding Plans which describe the system mission and its fielding requirements, including personnel needs;

8. Operational & Organizational (O & O) Plans which describe the system type, its mission, and its maintenance concept, and occasionally, its maintenance strategy;

9. Joint Element Mission Need Statement (JEMNS) which contains O & O information and required operational capabilities;

10. Qualitative and Quantitative Personnel Requirements Information (QQPRIs) which indicate the types of personnel required to operate and maintain the system;

11. System MANPRINT Management Plans (SMMPs) which describe how the system MANPRINT program will be handled, as well as data concerning expected MOSs and their current abilities and training profiles;

12. The Army MARC Maintenance Data Base (AMMDB) which indicates the maintenance MOSs associated with a system and their yearly maintenance manhours (which can be converted into the direct productive maintenance manhours) for the system; and

13. Other assorted planning documents, such as Letters of Agreement (LOAs) and Joint Service Operating Requirements (JSORs) which supply information about system mission, use, and maintainability.

For no system were all of these documents and sources available. However, there are overlaps in the sources such that in many cases information concerning an elemental factor appeared in multiple sources. The major difficulty with using different sources for the same type data is that occasionally the value for the elemental target factor differs between sources due to the impact of intermediate decisions which have been made. Table 4 in Appendix E depicts each data source and the systems for which each source was available to us. If the source was dated, the date is included in the table. Our data sources were supplied to us by the commodity commands, proponent schools, and the program managers associated with our target systems.

Data for dependent variables. All of the data for the dependent measures came from the Sample Data Collection (SDC) data bases maintained by the proponent commands. SDC data are collected for target systems over several years. These data are comprised of items such as mean time to perform maintenance tasks by MOS and/or level, the operational availability of the system, the total manhours necessary to maintain the system, and the mean time between failure rate for the system. Some commands collect all of the above items on their target systems, other commands collect a subset of the above items or include other items in their data. The Army uses these data to determine system design problems and requirements for modifying maintenance manpower.

Data coding. During data gathering and subsequently, we examined the data for completeness and comparability on our selected factors and variables. What we found was extreme inconsistency in the level of detail and availability of information for same types of documents or sources for the different systems. There was also a lack of consistency in definitions for data items. For example, mean time to repair might include both scheduled and unscheduled maintenance for one system, but only unscheduled maintenance for another.

In other cases, the definitions or components of the factor might be stated for one system, but not for another. This was especially noticed for one factor that was considered and discarded, Operational Availability. The planned operational availability for a system appears in the ROC. The actual operational availability is also monitored by most the commodity commands as part of their SDC data collection. However, in only one source document (HMMWV JEMNS) was the operational availability computationally defined for a system. One could assume that the same computations, with the equation elements defined as they were for the HMMV, occur anytime operational availability is referred to, but we received some indication that there are multiple ways of computing operational availability which would result in different values for availability (Narva, personal communication).

The data were found to fit three categories: (1) available and comparable across systems; (2) missing for some systems; and (3) available (or partially available), but not directly comparable. In cases in which data were available and comparable, we did not need to do anything but record the data. In situations in which data were missing, we had to decide whether the missing data could be derived from sources from similar systems or should be assigned a value for "missing" and excluded from the analyses.

In cases in which it seemed reasonable to substitute data from similar systems or similar processes or personnel, we did so. For example, we had some planning data for the Commercial Utility Cargo Vehicle (CUCV) which seemed appropriate to application to the High Maneuverability Mobile Wheeled Vehicle (HMMWV) for which we were missing those data. We made the decision to substitute data because of similarities between systems and expected system OPTEMPO, as reflected in documents we did have. In another case, we did not have SDC task time data available separately for different MOSs, but we had data across MOSs at a maintenance level. Therefore, we used the means across MOSs for the individual MOS categories.

In the situation in which we had similar but not directly comparable data (for example, mission duration in miles versus hours or rounds), we would scour the data for indications of ways to convert the different units to a single one. The selected method was system-dependent, but resulted in values that could be compared with other systems. Sometimes the SDC data showed the number of hours, miles, and rounds over which the data were recorded. Given this information, we could develop hour, round, and mile equivalencies. In other cases, within the planning documents one factor would be given in one set of units, and another in that same set and another set. With this information we could calculate the equivalencies for which we were looking.

Finally, there were times in which the values we derived were estimates based on a set of assumptions and computations. For example, the actual yearly maintenance manhours associated with a system does not appear on most of the SDC outputs for our target systems. However, these data can be approximated by dividing the total manhours for each MOS over all the examined tasks (test, inspection, remove and install, replace, repair, service, overhaul, and other such as painting) by years (often converted from hours) over which the maintenance took place. The assumption in this particular example was that all the maintenance manhours were accounted for in the listed tasks.

We also manipulated the annual maintenance manhours (AMMH) found in the AMMDB to produce Direct Productive Annual Maintenance Manhours (DPAMMH) for the MOSs who were expected to work on our target systems. We performed this manipulation by dividing the AMMH by constants associated with different MOSs and at different levels of maintenance (Unit or AVUM, Direct Support, AVIM, or General Support) listed in the AMMDB document (1989). We undertook this conversion because most of the planning documents present MOS manhour requirements in terms of DPAMMH, and we were comparing the documents to the AMMDB to ensure congruity.

Another procedure we undertook was the generation of planned task times by MOS and maintenance level. For three systems (the M1A1, the M2A1, and the UH-60A) we had these data directly from LSAR information we accessed from the MANPRINT data base maintained by the Material Readiness Support Activity (MRSA). Unfortunately, comparable data for our other systems have yet to be added to the data base and were not available from either MRSA or the U.S. Army Logistics Center. In order to have comparable data for our other target systems, we acquired MACs for these systems. Each MAC lists the system maintenance tasks to be accomplished by component and task type, the maintenance level that will perform the task, and the length of time the task should

take. The data appearing in MACs are derived from LSAR task data. To convert the MAC data into data comparable with the LSAR information, we had to assign an MOS to each task listed in the MAC at each maintenance level. We identified the MOSs associated with each system through examination of the system BOIP and other documents, the AMMDB, and the CROSSWALK report associated with the system. Once we knew which MOSs were to maintain the system, we reviewed their taskings as described in the Military Occupational Classification and Structure (1989). We compared these MOS taskings with the tasks listed in the MAC and assigned the system-associated MOS which seemed appropriate for performing the task. For example, if the MOS tasking indicated a responsibility for the maintenance and repair of all hydraulics for the system at the direct support level, we would assign all direct support level hydraulic tasks to that MOS.

In addition to the above steps taken to produce a useable data set, we had to categorize MOSs, system types, and system uses in order to compare them. For each system, we examined all the planning data and other indicators of maintenance MOSs associated with the system. We then composed a list of all MOSs and their titles. We also examined their tasking descriptions as they appear in the Military Occupational Classification and Structure (1989) to determine the types of tasks performed or equipment repaired. After this initial identification process, we sorted the MOSs into ten general categories which reflected the types of systems upon which they worked. These categories appear in Table 5 of Appendix E. Once we had established categories, we assigned each identified maintenance MOS to a category, by number. These assignments are shown in Table 6 of Appendix E.

Since we wished this analysis and its results to be applicable to system types rather than to specific systems only, we decided to categorize our target systems by type. These types and their associated codes appear in Table 3 in Appendix E. Table 3 shows each system with its associated code.

Finally, we categorized how the system was used, in order to capture some of the system design aspects which are implied by use. The system use categories are shown in Table 7 of Appendix E, with Table 8 showing the use codes associated with each system.

To give a concrete example of our data coding process, let's look at the way we proceeded with the M977, HEMTT. For this system, we had the following documents:

1. The JSOR in lieu of the ROC and O&O Plan.

2. The system BOIP.

3. The system QQPRI.

4. The system MAC.

5. FOOTPRINT reports for the maintenance MOSs associated with the HEMTT.

6. The AMMDB.

7. SDC data.

To define the system type and use, we examined the JSOR which describes the system and its mission. We also identified the rate, or number of hours per year, the system was to be operated as 8520 hours per year. This rate was based on an assumption of continuous use and ten days of down time per year as indicated by the Mean Miles Between Failures converted to Mean Time Between Failures identified in the JSOR. This value did not account for stand-by time, which for the HEMTT was indicated as 1460 hours over 365 days. We did not use a value that included the stand-by time because none of our other systems indicated the associated stand-by time.

To determine the MOSs that would be involved with the maintenance of the HEMTT, we examined the BOIP. The BOIP also supplied us with the system line item number which allowed us to examine the AMMDB for the annual maintenance manhours associated with each of the maintenance MOSs at the different levels of maintenance. The AMMDB gave us guidance in how to convert the annual maintenance manhours into direct productive annual maintenance manhours.

Once we had a list of MOSs, we turned to the FOOTPRINT reports to identify the MPT information associated with these personnel. The FOOTPRINT reports supplied for each MOS: (1) the mean AFQT score, (2) the percent of personnel retained from the first to the second term of duty, (3) the percent of high school graduates, (4) the number of personnel authorized in the past year, (5) the number of personnel operational in the past year, and (6) the length of training of the basic course for the MOS.

To determine LSAR task times for each MOS, we examined the <u>Military Occupational Classification and Structure</u> for descriptions of the jobs performed by each HEMTT-related maintenance MOS at each level of maintenance. We then examined the MAC for the HEMTT and identified which tasks would be performed by each of the MOSs and at what maintenance level, based on the MOS job description. Once all tasks we classified, mean times for each task category for each MOS, at each maintenance level were calculated.

Once we had identified the planning data, we examined the SDC data. For the HEMTT, we did not have task data separated out for each MOS. However, we did have task time at each maintenance level. In the case of the HEMTT, we used these data to represent all MOSs at a level who performed the task type. For example, if had determined through our examination of the documents that 63W's and 63Y's were supposed to perform inspection tasks at the unit level, and the mean time for inspection tasks at the unit level was .5, we would assign a value of .5 to inspection tasks for both the 63W and the 63Y MOS at the unit level. It should be noted that for some systems, we did have SDC data to the level of the specific MOS at a specific maintenance level; in those cases, we used the data that were given in the reports, with the only manipulation consisting of finding the mean task time over subsystems or components.

Our steps, as described above, resulted in 160 unique system type by MOS type by maintenance level cases. These data items were the ones used in our analyses.

Analyses and Analytic Aids

We undertook several different types of analyses and developed various aids to determining the validity of our analyses and the importance of the independent factors. Each of these analyses and aids are described below.

Multiple regression. Our selected analytic approach, as mentioned earlier, was linear multiple regression. We wished to develop a set of equations in the linear form, one to predict each of our dependent measures. Each equation would contain the subset of our selected elemental factors that best predicted the dependent measure. The elemental factors within the equation would be modified by weights and, as normal in a linear equation, a constant would be added.

We initially planned to test a saturated linear multiple regression model, in which all possible interaction terms were present, for each of our dependent measures. However, we reconsidered this approach when we realized that we had 45 independent factors after the development of dummy variables to represent the categorical factors. Because of the number of factors under consideration, we felt that the results of testing a fully saturated model would be likely to be uninterpretable. Therefore we decided to initially investigate only the main effects of our independent factors. In the event that one or more of these models did not account for more than 60 percent of the variance of the dependent measure, we would include selected interaction terms in the production of the model to determine if such interaction terms increase the predictiveness of the equation.

Testing a model in which only a subset of the interactions are included requires having a method for intelligent selection of terms for inclusion. We felt that the only interaction terms we could include into our equations were ones supported by previous research by Stermer (1986) and Jones, et al. (1986) who found that aptitude interacts with length of training to impact performance.

After examining various possibilities for software to perform these analyses, we decided to use SPSS PC+ because of its speed, data handling capabilities, ease of use, and multiple methods for building a multiple regression equation. For building our equations, we selected stepwise insertion of the factors into the equation. In this procedure, each factor is entered into the equation based on the strength of its correlation with the dependent measure and excluded from the equation based on either the probability that there is no significant relationship between the independent and dependent variables or the computed F statistic associated with the factor. In other words, during the regression analysis, SPSS PC+ computes the goodness of fit co-efficient, R-squared, for the equation during each step in which a factor is entered into the equation. The program then tests the hypothesis that population R-squared for the factor just entered is not significantly different from zero. This test results in an F statistic and a probability

associated with it. SPSS PC+ uses these results to determine whether or not the factor should be included into the equation during stepwise equation development.

The stepwise method was chosen over others such as the insertion of all factors at one time, because it allowed us to see the impact of each elemental factor as it was added to the equation through examination of its resulting statistics, such as R-squared. Changes in R-squared indicate the amount of variance accounted for by the factor just entered into the equation.

Since we had numerous missing data items which we felt could not be generated from examination of other data, we deleted missing data in a pairwise fashion for the analyses. In pairwise deletion, when each factor is entered into the equation, only the data items present for the factor are used. This results in some factors being supported by more data items than others. Our other option for handling data was to substi⁻ute the mean for the data elements for a factor for the missing data items for ti ⁻ .actor and then run the analysis. This procedure was rejected because it had the potential for masking true relationships among factors, because it would have artificially reduced the between case variance due to the extensive number of missing items that the means would replace.

<u>Planned versus actual burden</u>. In addition to performing the described multiple regression analyses, we compared the predicted task times found in the LSAR task data and MACs with the SDC task time data. This was accomplished by producing and examining a correlation matrix containing all the variables, both independent and dependent, of interest. We felt that such the interpretation of the outcome of this procedure would be indicative of the Army's ability to plan task times.

When producing the correlation matrix, we used pairwise deletion of missing cases to control for lack of data. This occasionally led to situations in which the correlation could not be computed for two variables due to the total lack of cases for the pair.

<u>Metafactor weight development</u>. One of the requirements for this effort was the development of weights for both the metafactors and the elemental factors comprising them. The multiple regression procedure produces two types of weights for each elemental factor in the developed equation. The regression co-efficient, referred to as the "B" weight, is a co-efficient to be applied to raw data reflecting the factor. The set of "B" weights developed for each equation were the ones we could use for a trade-off tool in which a user will be entering raw data of the type we used. In this way, we were able to generate weights for the predictive elemental factors.

The other type of weights produced by multiple regression are the factor "Beta" weights. Beta weights are co-efficients for the equation's factors similar to "B" weights. The difference between the two types of co-efficients is that Beta weights are calculated based on data sets in which all data items have been converted to standardized scores (Z-scores). The set of Z-scores for each factor has a mean of zero. Standardizing the data in this way places them on a common scale. The Beta weights are calculated from data which are on a common scale across factors. (They can also be calculated directly from

the "B" weights using the equation $BETA_k - B_k (S_k/S_y$, where S_k represents the standard deviation for the factor values and S_y is the standard deviation for the dependent variable values.) This results in Beta weights which are directly comparable with each other in terms of relative predictiveness. (They are not absolutely comparable due the impact of inter-correlations among the independent factors.) In other words, one can rank order the elemental factor Beta weights by size to produce a scale of relative importance with regard to prediction of the dependent measure. This also means that the elemental factor Beta weights representing a metafactor can be combined, at least for examination of relative predictiveness of the metafactors, to produce a metafactor weight. For example, if one elemental factor that comprises a metafactor has a Beta weight of 2 and another, also comprising the same metafactor, has a Beta weight of 1, if there is no interaction between these two elemental factors, the weight for the metafactor which is comprised of the two elemental factors would be 3. This weight could be rank ordered with the other weights to reflect predictiveness of the metafactors.

Certainty ratings development. One issue that is important to consider within the context of a method in which data are manipulated is the certainty that one can place on the results. In this effort, we were working with both missing and manipulated data, as well as some complete data. Therefore we determined that it was necessary to assign certainty ratings for each factor weight produced by our analyses for our equations. We based our ratings on the availability of data to support the given factor weight.

We constructed a three-point certainty scale as follows:

1 - little data (less than 50 valid data items);

2 - medium amount of data (more than 50 valid data items, but less than 100); and

3 - high quantity of data (100 or more valid data items).

After developing this scale, we examined each elemental factor in each regression equation and determined, and assigned, to it a certainty rating. To assign certainty ratings to the metafactors represented by the elemental factors in our equation, we took the mean of the certainty ratings assigned to the elemental factors that comprised each metafactor. For example, if metafactor 1 was comprised of elemental factors 2, 3, and 5, rated 1, 2, and 3, respectively, the metafactor certainty rating would be 2.

Common metric development. One requirement for this effort was the development of a common metric on which to place the metafactors and their weights. The method we selected for doing this has been alluded to in the section on Weight Development.

There is one type of metric which is applicable in this situation, and it is derived from the use of the elemental factor Beta weights. As mentioned above, the elemental factor Beta weights are based on the conversion of the data cases to a common metric as represented by standardized scores. This conversion results in elemental factor weights which reflect a common metric and scale, and thus have absolute values which are directly comparable, in a

relative sense, to each other. This means a factor of a weight of 4 is approximately twice as predictive as a factor with a weight of 2. Any combination of these weights, as in the generation of metafactor weights, would be on this same scale.

Product Development

One of the final outcomes of this effort is a trade-off tool that is to be used by Army personnel to predict the results of their planning decisions concerning maintenance for a system. This tool is to be easy to use and fast with regard to its output generation. It should allow the user to input readily available data. We investigated three types of trade-off tools and formats which might be suitable for this effort. Each one is described in the following paragraphs.

Spreadsheet. We examined the possibility of embedding the developed regression equations into a spreadsheet format for use as a predictive tool. We felt two types of spreadsheets were possible choices: (1) one for user-supplied MPT and system factors, allowing for the prediction of actual task times; and (2) one for user-supplied actual task times and some system factors to allow for constraint satisfaction.

Developing a spreadsheet would require the use of a spreadsheet program such as LOTUS 1-2-3. In addition to embedding the equations in the spreadsheet, a user guide would have to be developed to explain to the user: (1) the labels and headings appearing in the spreadsheet; (2) the steps to take when using it; (3) what types of predictions can be made via use of the spreadsheet; and (4) the types of data to be entered.

There are two drawbacks related to this type of tool. First of all, to be able to perform both prediction of values for our outcome variables (actual maintenance times) and to satisfy missing constraints given values for the outcome variables (and a subset of values for the input, or planning, factors), one needs: (1) multiple formulas for each cell, one that predicts the cell's value based on data in other cells and the second set of formulas for predicting the contents of other cells based on the initial cell's value in combination with other cell values and a method for selecting among those rules; or (2) multiple spreadsheets and rules for spreadsheet selection.

The second drawback of a spreadsheet tool is that it cannot convey the temporal relationships among decisions made about the factors involved. However, this may not be such an extreme drawback if the user is knowledgeable in the acquisition process and is more concerned with the ultimate effect of decisions, rather than the order in which they are made.

Neural network pattern matcher. A second type of tool that we examined was a pattern matching tool based on a trained neural network. This type of tool could be used for both constraint satisfaction of the planning factors, given values for the maintenance performance variables and some of the planning factors, as well as prediction of our maintenance performance variables. However, to implement such a tool, one must: (1) select the

appropriate neural network algorithms, number of neuronal layers, and constraints; (2) train the network on a data set including input patterns (predictor factors) and output patterns (dependent variables); and (4) embed the resulting network into an easy-to-use interface.

Although a neural network pattern matcher alleviates the need for multiple equations for output prediction and constraint satisfaction, it has the major problem of requiring many more resources for development than a spreadsheet implementation. The major drain on resources for the development of this type of tool is the programming effort required to produce a user interface for the network.

Rule-based expert system. A third type of tool which we considered as an output of this project was a rule-based expert system. There are expert system shells such as VP-Expert, which can import data from a spreadsheet or ASCII file and use the data to generate a knowledge base containing rules which describe the data. These rules take values for the identified factors and then generate an outcome based on those rules and values.

The major drawback to this alternative is that most expert system shells cannot extrapolate conclusions based on data values not appearing in their rules. Therefore if one entered a factor value not appearing in any rules, the program would indicate an error. This is not a problem if one has all possible data sets that might occur available to place in the knowledge base. In our situation, we have a non-inclusive set of 160 cases.

Tool to Be Developed

After examining the possibilities for tool development, we felt that the initial tool to be developed should be a spreadsheet format in which the multiple regression equations would be embedded. This format would allow a user to develop various data sets or cases representing maintenance planning factors, input them into the spreadsheet, and be given a prediction of mean times to perform actual maintenance tasks. Additional spreadsheets would be developed to allow constraint satisfaction, with each spreadsheet representing a tool for the prediction of one planning factor based on other planning factors and maintenance performance.

Given adequate resources, we felt an extension of the spreadsheet set could be developed at some point into an integrated constraint satisfaction tool. For this tool, the user would enter maintenance task times and various planning factor values in response to a series of queries; the program would then access the correct spreadsheet, fill in the missing cells, and calculate the result. This would require developing a set of spreadsheets and rules for spreadsheet selection based on responses to probes by the user. The rules could be stored in a knowledge base and manipulated by an expert system shell.

Results

Multiple Regression Analyses Results

Two sets of regression analyses were performed, one for our elemental factor and metafactor analyses and one for tool development. In the first set, ten regression analyses were performed using a stepwise method to construct the equation comprised of elemental factors predicting actual mean times to perform a maintenance task. No interaction terms were included in these first ten analyses. Tables 9 through 18 in Appendix E display results of these analyses. These tables indicate:

1. The dependent measure for equation.

2. The elemental factors included in the equation.

3. The constant for the equation.

4. The regression co-efficients (or weights) associated with the elemental factors ("B" co-efficients) and applied to the raw data.

5. The standardized Beta co-efficients (or Beta weights) for the elemental factors whose absolute values indicate the relative importance of the independent factors in predicting the dependent measure.

6. The amount of variance in the dependent measure accounted for by the elemental factor (based on the adjusted change in R-squared at the step in which the factor was entered into the equation).

7. Correlation information including the correlation co-efficient computed between the elemental factor and the dependent variable, the number of cases included in the multiple regression and correlation analyses for the factor-dependent variable pair, and the probability associated with the correlation co-efficient.

8. The certainty rating for the elemental factor weights.

9. The multiple R (reflecting the combined correlations of the factors with the dependent measure) for the equation.

10. The R-squared for the equation which indicates the proportion of dependent measure variance accounted by the equation without adjusting for inter-dependence of the independent factors.

11. The adjusted R-squared for the equation which indicated the proportion of variance accounted for by the equation after adjusting for factor independent inter-dependent an adjusted R-Squared value near 1.0 indicates the equation is very good at predicting the dependent measure).

12. The standard error for the equation indicating how much the regression co-efficients will vary across different samples.

13. The F statistic and its probability for the equation which indicates whether or not the equation can account for a significant amount of the dependent measure variance.

The first factor entered into each equation was the one which fit the selected inclusion criteria of: (1) the minimum value of the F statistic needed to be entered into the equation (called the FIN), which was set at 3.84, and (2) the minimum probability for the F statistic indicating the factor should be entered into the equation, called the PIN or probability of F-to-enter, which was set at .05. In the cases of the equations for actual replacement time, actual service time, actual repair time, and actual maintenance manhours, the PIN default was changed to .1, because no, or very few, factors were initially entered into the equation.

Subsequent factors were entered into an equation based on whether it met the criteria for removal from the equation. In order not to be removed from the equation, a factor had to have an F statistic value or 2.71 or greater and a probability associated with the F statistic of .1.

As one can see from Tables 9 through 18 in Appendix E and summary Table 3 below, these first analyses resulted in equations with a wide range of predictive capability as reflected by the complete predictiveness of the equations for actual mean replacement time (ACT_RPL), actual mean time to test (ACT_TST), actual mean time to perform "other" tasks (ACT_OTH), and actual mean time to overhaul (ACT_OVRH), as compared to minimal predictiveness of the equation for actual mean time to remove or install (ACT_R_I) whose included elemental factors accounted for .19 of the variance.

It was also found that for the dependent measures of actual replacement time, actual mean times for "other" tasks, actual mean time to overhaul, and actual mean time to test, there were factors that could be included into the equation even after all of the dependent measure variance had been accounted for. This indicated that there were multiple predictive equations possible for those dependent measures. The statistics reported for these dependent measures reflect the results for the step prior to accounting for 100% of the variance, since once all the variance has been accounted for, SPSS PC+ cannot calculate F statistics for other factors entered into the equation.

The elemental factor that appeared most frequently in the equations was retention rate, which occurred in seven equations. This factor accounted for seven percent of the variance or more in all of these equations. Retention rate is a personnel factor indicative of maintainer experience, as well as an indicator of availability of experienced manpower. This factor was negatively related to the dependent measures in that as the retention rate became smaller, the task times increased.

To summarize, we found the two most predictive elemental factors in terms of variance accounted for each equation to be as follows (and as shown in summary Table 4).

Table 3. Predictive Ability of Equations

Measure	Adjusted R-Squared
Mean Time to Repair	.34
Mean Time to Remove or Install	.19
Mean Time to Service	.44
Mean Time to Replace	.99
Mean Time to Test	.94
Mean Time for Other Tasks	.91
Mean Time to Overhaul	.95
Mean Time to Inspect	.45
Mean Time to Adjust	.21
AMMH	.37

For the dependent measure, actual mean time to repair (ACT_RPR), the first top elemental factor was the case of three maintenance levels (LOM1). It accounted for 20 percent of the variance and had a certainty rating of 3. The predicted time to overhaul (PRED_OVR) as appearing in the LSAR task and MAC data was the second most important elemental factor. It accounted for 10 percent of the variance.

In the case of the dependent measure, actual mean time to remove or install (ACT_R_I), the elemental factor accounting for the greatest proportion of the variance was the predicted time to service (PRED_SER) as extracted from the LSAR and MAC data. This elemental factor accounted for 11 percent of the variance and had a certainty rating of 1. The second elemental factor appearing in this equation was predicted time to overhaul (PRED_OVR) which accounted for 8 percent of variance. PRED_OVR also had a certainty rating of 1.

When actual mean time to service (ACT_SERV) was the dependent measure, the first top elemental factor was again PRED_OVR, accounting for 18 percent of the variance with a certainty rating of 2. The second most predictive elemental factor was the case in which the maintenance personnel maintained hydraulic and pneudraulic systems (MOS1). This elemental factor accounted for 7 percent of the variance and had a certainty rating of 3.

Table 4. Most Predictive Elemental Factors

Dependent Measure	Factors	Amount of Variance Accounted For	Beta Weight	Certainty Rating
Mean Time to Repair	LOM1	.20	.38385	3
	PRED_OVR	.10	.38325	2
Mean Time to Remove/ Install	PRED_SER	.11	.40829	1
	PRED_OVR	.08	.33045	1
Mean Time to Service	PRED_OVR	.18	.61535	2
	MOS1	.07	-.20268	3
Mean Time to Replace	RET_RTE	.36	-417.8538	2
	PRED_R_I	.33	140.94357	1
Mean Time to Test	PRED_RPR	.63	76.50056	2
	RET_RTE	.21	-205.0936	2
Mean Time for Other Tasks	PRED_OVR	.17	20.39984	1
	PRED_R_I	.16	8.73244	1
Mean Time to Overhaul	PER_HS	.35	-1.72049	1
	PRED_OVR	.33	20.52509	1
Mean Time to Inspect	SYS5	.16	.52180	3
	MTL2	.09	.27934	3
Mean Time to Adjust	RET_RTE	.21	-.47164	2
Annual Maintenance Manhours	MOS9	.20	.36467	3
	RET_RTE	.10	-.37485	3

For the dependent measure of actual mean time to replace (ACT_RPL), retention rate (RET_RTE) accounted for the greatest amount of variance (36 percent) over all other elemental factors in the equation. It had a certainty rating of 2. The second most predictive elemental factor was the predicted time to remove or install (PRED_R_I) derived from LSAR and MAC data. This factor accounted for 33 percent of the variance and had a certainty rating of 1.

In the case of actual mean time to test (ACT_TST) as the dependent measure, the most predictive elemental factor was the predicted repair time (PRED_RPR) derived from LSAR and MAC data. It accounted for 63 percent of the variance and had a certainty rating of 2. Retention rate, accounting for 21 percent of the variance, was the second most predictive elemental factor in the equation and had a certainty rating of 2.

With regard to the dependent measure actual mean time for other tasks (ACT_OTH), PRED_OVR was the most predictive, accounting for 17 percent of the variance with a certainty rating of 1. PRED_R_I accounted for 16 percent of the variance with a certainty rating of 1, also.

In the equation for actual mean time for overhaul (ACT_OVRH), PRED-OVR, the elemental factor accounting for the second greatest amount of variance (33 percent) had a certainty rating of 1. The elemental factor percent high school graduates accounted for 35 percent of the variance and also had a certainty rating of 1.

For the dependent measure of actual time to inspect (ACT_INS), the fact that the system was a tracked fighting vehicle was the most predictive elemental factor, accounting for 16 percent of the variance with a certainty rating of 3. Situations in which maintenance was performed at the direct support level also were predictive, accounting for 9 percent of the variance and having a certainty rating of 3.

The equation for actual time to adjust (ACT_ADJ) had only one elemental factor entered, retention rate, which accounted for 21 percent of the variance. This factor had a certainty rating of 2.

The final equation, for the dependent measure of actual annual maintenance manhours (ACT_MMH), has the most variance accounted for by the cases in which the maintainers' tasks were on artillery (20 percent) with a certainty rating of 3. Retention rate accounted for the second largest amount of variance at 10 percent and had a certainty rating of 3.

Because of the lack of predictiveness of the equations for some dependent measures, we determined the need to develop equations containing interaction terms for some of the factors. The factors selected for inclusion as interactions were aptitude, as reflected in mean AFQT scores and training as represented by length of training. As indicated in the Approach section of this report, these factors have been found to interact. We included this interaction term in the equations for ACT_RPR, ACT_ADJ, ACT_SERV, ACT_INS, and ACT_MMH. We found that for only ACT_INS and ACT_MMH did the inclusion of the interaction factor make a difference. The equations for ACT_INS and ACT_MMH resulting from these analyses are presented in Tables 19 and 20 in Appendix E. The results from these analyses are misleading, however. The result for ACT_INS, when the interaction for training length and AFQT score is included, is an equation with many factors in it that are not included in the equation without the interaction. It is not clear why there is such a large difference between the equations. For ACT_MMH, the inclusion of the interaction term resulted in the masking of the effect for training length that appeared in the initial equation. In the case of ACT_MMH, the equation produced when the interaction was included accounted for only 6 percent more variance than the

initial equation. Because of these misleading results, we feel that the equations without the interaction term included should be used for all subsequent analyses and procedures.

As mentioned earlier in this report, retention rate, although it appears as the number one factor in only one equation, accounts for 10 or more variance in five equations, those for ACT_RPL, ACT_TST, ACT_OVRH, ACT_ADJ, and ACT_MMH. Retention rate is a measure of both availability (what percentage of the total maintainer pool will be experienced personnel?) and personnel characteristics (what experience level will the maintainers be at?). It is also logical that if one becomes more skilled at a task, through experience, one becomes faster at performing the task.

The regression equations indicated some other interesting findings. Although we did not specifically examine the individual factors in each equation for the significance of amount of variance they accounted for, we did observe some important trends. (However, since our regression equations were constructed using a stepwise insertion method, if a factor was entered into the equation, it necessarily accounted for a significant amount of the variance.) For example, in all equations with a time-to-perform dependent measure (as opposed to Annual Maintenance Manhours) in which any of the MPT factors of training length, retention rate, mean AFQT score, or proportion of high school graduates appear, increases in these factors decrease the time to perform the maintenance task. This result is not unexpected, since one would hope that as maintainers increase in experience and basic abilities, they would perform tasks more quickly.

For four of the dependent measures, we found an effect related to the systems under examination. In the cases of the dependent measures ACT_RPL and ACT_OTH, maintenance times for transport helicopters and large guns were less than for other systems. Time to test (ACT_TST) was less for tank systems, large guns, and scout helicopters, as compared to the other systems under examination. For ACT_OVRH maintenance was performed on a large gun more quickly than on other systems, with scout helicopters requiring the most time. There was no real difference between the times for overhaul on the other systems.

For ACT_SERV and ACT_RPL, we found that if the tasks were performed at the unit level, they required more time than if performed at any other maintenance levels. Also, for ACT_RPL (and for ACT_TST and ACT_OTH), we found maintenance was at the Intermediate level required less time than if performed at other levels.

Finally, if we examine the effect of different MOSs on task times, we find that for ACT_SERV, performance by hydraulics/pnuedraulics personnel is performed more quickly than service tasks by other maintainers. In the case of ACT_RPL, all MOS groups are much faster than one other group, the armorers. With regard to the performance of testing tasks (ACT_TST), we found that the related MOSs of avionics, powertrain, and electrical systems personnel were much faster than maintainers of the other types of MOSs. The other MOS types did not appear in the equation, so they are not different from each other with regard to performance times. For overhauling the system (ACT_OVRH), hydraulics/pnuedraulics and structural personnel require less time to perform

their tasks, than other maintainers. Finally, we found that structural maintainers take longer to inspect the system, than other types of maintainers.

Although we observed the described trends, for the most part we cannot give precise interpretations of them. It is likely that for the findings related to systems, maintenance level, and MOSs, the correct interpretation could be generated based on a thorough examination of the differences: (1) among the systems and subsystems, and (2) the tasks to be performed by the various maintainer groups at the different levels of maintenance.

Metafactor Analysis

Factor Weight. Our multiple regression analyses resulted in factor weights for elemental factors included in each equation. These weights appear in Tables 9 through 18 of Appendix E.

The absolute values of the Beta weights for the elemental factors can be ordered numerically to indicate the relative relationships among the factors with regard to impact on the dependent measure. It may be noted that, for some equations, the order of Beta weights does not match the order of predictiveness derived from the amount of variance accounted for by the factors. This difference is the result of high correlations among the elemental factors in the equations. These correlations result in cases of multi-collinearity in which the Beta weights associated with elemental factors in question may not be uniquely determined (as one might suspect for elemental factors comprising a higher order metafactor). Therefore, one must examine the Beta weights for elemental factors in conjunction with their R-squared values, which are indicative of amount of accounted variance. It is possible, in fact, that for the elemental factors, the ordering of R-squared values probably is a better indicator of dependent measure predictiveness than is the Beta weights ordering.

Through our examination of the generated regression equations, it was determined that in eight equations there was more than one elemental factor representing a metafactor present. These equations were for:

1. Actual Mean Time to Overhaul (ACT_OVRH);
2. Actual Mean Time for Other Tasks (ACT_OTH);
3. Actual Mean Time to Repair (ACT_RPR);
4. Actual Mean Time to Remove or Install (ACT_R_I);
5. Actual Mean Time to Service (ACT_SERV);
6. Actual Mean Time to Replace (ACT_RPL);
7. Actual Mean Time to Test (ACT_TST); and
8. Actual Annual Maintenance Manhours (ACT_MMH).

For metafactors represented by only one elemental factor in the equation, we took the standardized regression co-efficient (Beta weight) to represent the metafactor weight. When the metafactor was represented by more than one elemental factor, the metafactor weight was computed by adding the Beta weights of the elemental factors. This resulted in a set of relative metafactor weights for the equation. These metafactor weights for each equation are shown in Table 22 through 31 in Appendix E. In these tables, each equation is identified by its dependent measure. The dependent variable name is followed by a list of metafactors in the equation and the associated factor weights and certainty rates.

The two most important metafactors, based on the combined Beta weights for the elemental factors for each equation are shown in Summary Table 5 and are as follows.

For the dependent measure ACT_RPR, the combined metafactors of Operational and Organizational Plan and Maintenance Concept were of greatest importance with a metafactor Beta of .38385 and a certainty rating of 3. Almost as important, however, was the metafactor of Maintenance Profile with a Beta weight of .38325 and a certainty of 2.

The dependent measure of ACT_R_I contained elemental factors for only one metafactor, Maintenance Profile, with a Beta weight of .73874. This metafactor had a certainty rating of 1.

The equation for ACT_SERV contained elemental factors for four groups of metafactors. The metafactor with the highest Beta weight was Maintenance Profile at .99237 and a certainty rating of 2. The second highest absolute Beta weight was for Training System at .42497 with a certainty rating of 3.

With regard to ACT_MMH, the combined metafactors of tasks and Maintenance Profile had the highest Beta weight (.41420) for the equation. This group of metafactors had a certainty rating of 3. The metafactors BOIP and MOS had the second highest Beta weight of .36467, also with a certainty rating of 3.

In the case of the equation for ACT_RPL, the metafactors BOIP and MOS have a Beta weight of -1776.25, the absolute value of which is much larger than any other metafactor Beta weight. These metafactors have a certainty rating of 3. The metafactor, Maintenance Concept, has the second highest absolute Beta weight (-675.16) with a certainty rating of 3.

For the dependent measure ACT_TST, the metafactor of system maintenance characteristics had the highest absolute Beta weight (-819.54) with a certainty rating of 3. The next most important metafactor for this equation was the combined Operational and Organizational Plan and System. This metafactor pair had a Beta weight of -558.47 and a 3 for its certainty rating.

When ACT-OTH was the dependent measure, BOIP and MOS combined was the metafactor with the highest absolute Beta weight (-87.28) and a certainty rating of 3. Operational and Organizational Plan and System, was the metafactor with the second largest absolute Beta weight (-59.59) with a certainty rating of 3.

Table 5. Most Predictive Metafactors

Dependent Measure	Metafactor	Beta Weight	Certainty Rating
Time to Repair	O&O Plan/Maintenance Concept	.38385	3
			2
	Maintenance Profile	.38325	
Time to Remove/ Install	Maintenance Profile	.73874	1
Time to Service	Maintenance Profile	.99237	2
	Training System	.42497	3
Annual Maintenance Manhours	Tasks/Maintenance Profile	.41420	3
	BOIP/MOS	.36467	3
Time to Replace	BOIP/MOS	-1776.25	3
	Maintenance Concept	- 675.16	3
Time to Test	System Maintenance Characteristics	- 819.54	3
	O&O Plan/System	- 558.47	3
Time for Other Tasks	BOIP/MOS	- 87.28	3
	O&O Plan/System	- 59.59	3
Time for Overhaul	O&O Plan/System	- 31.88	2
	Tasks/Maintenance Profile	- 30.39	1
Time to Inspect	O&O Plan/System Maintenance	.52180	3
	Concept/Maintenance Profile	.27934	2
Time to Adjust	Availability	-.47164	2

The metafactor of Operational and Organizational Plan and system had the largest absolute Beta weight for the ACT_OVRH equation. The Beta Weight was -31.88 with a certainty rating of 2. The metafactor of Tasks and Maintenance Profile had the second largest Beta weight (30.39) and a certainty rating of 1.

The equation for ACT_INS also had the metafactor of Operational and Organizational Plan and System as having the largest Beta weight (.52180) with a certainty rating of 3. The metafactor of Maintenance Concept and Maintenance Profile had the second highest Beta weight (.27934) and a certainty rating of 2.

For the final equation (ACT_ADJ), there was only one metafactor described by the elemental factors. This was the Availability metafactor which had a Beta weight of -.47164 with a certainty of 2.

As can be seen from Table 6, the two metafactors of importance appear to be O&O Plan and Maintenance Profile. Since Maintenance Profile is comprised of the LSAR task time factors, it is reasonable to expect that task times used for planning should be predictive of actual task times. The O&O Plan metafactor reflects the system designator and use. The fact that it is such an important metafactor indicates that system decisions play a very important role in the performance of maintenance.

The most unusual finding with regard to the metafactors is that the MPT-related metafactors do not play as important of a role in the determination of maintenance performance as some of the other metafactors. What this finding could mean is that although there are strong relationships among the MPT elemental factors and maintenance performance, overall it may be the O&O Plan and the Maintenance Profile, and the processes by which they are developed, which have the major influence on maintenance performance.

We should also stress that the metafactors are but labels for groups of related elemental factors. We could possibly try categorizing and labeling groups of metafactors more so than previously done. (In Evans & Roth, 1988, the metafactors were classified as to their influence on other metafactors in terms of being drivers, intermediate, or driven; in the first phase of this effort, we classified the metafactors as to whether they represented names of documents or types of information contained in documents.) However, this tactic of classifying the metafactors, although appealing, might obscure the factors of actual importance, the elemental factors, and the relationships among the elemental factors implied by their categorization by metafactor.

Supporting Analyses

Certainty Ratings. Certainty ratings were assigned to each elemental factor appearing in the developed equations. This rating for each factor is displayed in the last column in Tables 9 through 18 of Appendix E. The mean rating for each equation is shown Table 32. In all but two cases, the mean rating for the equation was 2.0 or greater, indicating that we had moderate confidence in our data. Certainty ratings for the metafactors were also

calculated. These ratings appear in the last column on each of Tables 22 through 31 of Appendix E.

Common Metric. A common metric was developed for each regression equation in order to compare the relative importance of the factors appearing in the equations. The common metric was developed by standardizing all the scores associated with the factors in the equation to produce Z-scores. The mean of Z-scores is zero and the standard deviation is one. Thus the data sets associated with each factor can be placed on a comparable scale. These Z-scores were then used to calculate a set of standardized regression co-efficients (Beta weights) for each factor in the equation. The Beta weights for the elemental factors appearing in the equations appear in Tables 9 through 18 of Appendix E. The Beta weights for the metafactors represented in the equations appear in Tables 22 through 31 in Appendix E.

The Beta weights for the elemental factors can be compared for each equation by taking their absolute values and rank ordering them (but be aware of the problem of multi-collinearity described previously). With regard to the metafactor Beta weights, it was found that the metafactor "Maintenance Profile" was the most relevant for two of the equations. This makes sense that this metafactor would be predictive of actual task times since it is comprised of the expected task times as found in the LSAR data. The "O & O Plan" metafactor also occurs in three equations as being most predictive of task times. This may be due to the fact that the O & O Plan metafactor is comprised of items such as number of maintenance levels which eventually impacts the allocation of tasks.

Other Analytic Results

We performed a correlation analysis to compare the relationships between predicted maintenance task times derived from the MACs or LSAR task data and actual times. The resulting correlation matrix is shown in Table 21 of Appendix E. The matrix contains the correlation co-efficients for each variable pair, the number of cases used to calculate the co-efficient enclosed in parentheses, and the probability associated with the co-efficient. This matrix also displays the relationship between predicted DPAMMH and AMMH. As one can see from the correlation co-efficients and their related probabilities, there are no significant relationships between the planned times and manhours and their analogous actual times and manhours.

A final analysis we undertook was a comparison of the MOSs specified in the planning documents to perform maintenance on a system and the actual MOSs who did perform the work. Tables 33 through 41 in Appendix E show for each target system, a list of MOSs listed in the planning documents and a list of the MOSs performing maintenance as indicated by SDC data. Table 42 presents: (1) the system designation, (2) the number of MOSs appearing in the planning documents for the system, (3) the number of MOSs appearing in the SDC data, (4) the number of MOSs appearing in both the planning and the SDC data, and (5) the percent of MOSs for which plans were made and who actually perform the maintenance.

As one can see from Table 42 of Appendix E, in many cases the MOSs which were planned for system maintenance were the ones that performed the maintenance, but often were supplemented by others. In a few cases (e.g., the M198 and M977), there was very little overlap between the planning of MOS use and actual use.

RIT-TOM

We developed a trade-off tool, the Requirements Integration Trade-Off Tool for Maintenance (RIT-TOM), based on a second set of multiple regression analyses. RIT-TOM allows one to make predictions concerning actual maintenance task times based on the predictor factors appearing in the multiple regression equations developed during this phase. RIT-TOM also allows one to predict a factor value based on the values for other factors and actual task times.

RIT-TOM is spreadsheet-based. The application software used to develop the tool is LOTUS 1-2-3 Version 2.0. The tool is comprised of several spreadsheet files which can be accessed via LOTUS and manipulated. There is one spreadsheet file for use when predicting actual maintenance task times based on predictor factor values, and one spreadsheet for prediction of each planning factor given the other planning factors and one actual maintenance task time. We have selected a subset of planning factors to include for prediction in order to reduce the number of spreadsheets with which the user would need to interact. The planning factors we have limited the prediction, for a system type and use and MOS type, to are:

1. Mean Armed Forces Qualification Test (AFQT) score (a measure of personnel quality);

2. Retention rate (a measure of personnel experience and manpower availability);

3. Length of training (a training system measure); and

4. Number of personnel of MOS who are authorized (a measure of manpower).

A new set of equations containing a reduced set of factors was developed for use in the production of RIT-TOM spreadsheets. For the spreadsheet to predict task times, we used equations containing MPT factors, but no LSAR task times. We did this to limit the number of inputs required and reduce possible confusion of asking for task times and outputting task times. The other spreadsheets, to be used for predicting MPT factor values, are generated from equations predicting the variable of interest for spreadsheets given actual task times. This was done so that we would be able to examine each MPT factor of interest for the spreadsheet, given task times. The resulting equations are shown in Table 43 of Appendix E. Their predictive capabilities appear in summary Table 6 below.

The equations used for the factor spreadsheets vary in the amount of variance accounted for, from a high of 94 percent, as reflected by the

adjusted R-squared, to an adjusted low of -81 percent. (The impossible value is probably due to the lack of data for some of the cells in the correlation matrix used during the analysis.)

If we compare the equations we developed for RIT-TOM, with those used in our overall analysis (see summary Tables 4 and 6), we find that the removal of the LSAR task times greatly reduces the predictive capabilities of our equations for task times. This finding indicates the strong relationship that exists between the task times planned for during the acquisition process (the LSAR task times) and actual time to perform these tasks in the field. What this means is that although the individual LSAR task times do not necessarily correlate very well with their associated actual task performance times (e.g., LSAR time to inspect does not correlate strongly with actual time to inspect), LSAR task times taken as a group, are very predictive of actual task times.

RIT-TOM has been delivered on a 5 1/4" double density, double-sided floppy disc. It assumes use on a MS-DOS system that has LOTUS 1-2-3 available for use with the tool. The RIT-TOM User's Guide appears in Appendix F. The user's manual explains the tool and its use. It also describes in detail the data types that need to be entered into each spreadsheet in the set. The manual assumes the user is familiar with LOTUS.

To interact with RIT-TOM, the user determines the item he wishes to predict. Based on this decision, he can refer to his user's manual to identify the spreadsheet file appropriate to his needs. The user then initiates LOTUS and selects the appropriate spreadsheet file. He then enters data into all cells on the spreadsheet other than the one he wants to predict, as directed by the user's manual. He then presses the calculate key (F9), and LOTUS will compute the desired value. If the user wants to test other data sets for prediction of this value, he will be able to without exiting the spreadsheet. If he wishes to copy these values to another spreadsheet in the set, he may do so using the appropriate LOTUS command.

Table 6. RIT-TOM Equations

Measure	Adjusted R-Squared
Time to Inspect	.58
Time to Test	.34
Time to Remove/Install	-.81
Time to Replace	.53
Time to Adjust	.08
Time to Repair	.24
Time to Service	.23
Time to Overhaul	.51
Time for Other Tasks	-.12
AMMH	.49
Authorized	.40
AFQT	.68
Retention Rate	.94
Training Length	.75

<u>Examples of RIT-TOM uses</u>. RIT-TOM can be used to answer several questions, for example:

1. Given system MPT requirements, what is the mean time to perform maintenance tasks for an MOS type?
2. Given system MPT requirements, what is the approximate annual maintenance manhours for an MOS type?
3. Given a mean time to perform a maintenance task, such as inspect, and the other system MPT requirements, what mean AFQT score will personnel with a particular MOS have?

We tested RIT-TOM on the above three questions. We did so by supplying RIT-TOM with an initial data set from one of our target systems. We would have preferred to use a system not utilized in our analyses, but the lack of data forced us to select one of our target systems for our test.

For question one, we entered our data set into the RIT-TOM MPTPRED.WK1 spreadsheet and had it predict mean task times for the 63B MOS (classified as type 8), working on the HMMWV at the Unit level. The data entered are shown in Table 44 of Appendix E. The predicted times and actual times as recorded by us during data gathering are shown in Table 45, with the difference between the two values indicated. As can be seen in Table 45, RIT-TOM is not extremely accurate. However, in most cases it overestimates the time requirements for task performance. It can be argued that over-estimation is more desirable than underestimation during planning because it is easier to reduce expectations at a later date than to increase them. The cases in which RIT-TOM underestimated, it was by less than three hours. Estimation errors and negative values can result from: (1) rounding procedures which were required to make the equations fit the constraints imposed by LOTUS, (2) the narrow range of data we are trying to predict, and (3) the much larger sizes of the B weights and co-efficient in relation to the values to be predicted. (The rounding problem might be solved by generating intermediate sums, which are then added for the final result.)

To answer question two, we also used the MPTPRED.WK1 spreadsheet. We entered the data for the 63G at DS level working on the HMMWV. The data for this type of person are shown in Table 46. The results of this analysis were an AMMH of 2721. The actual AMMH is 47.2. Thus RIT-TOM significantly over estimated AMMH. This might be due to the fact that AMMH really is related to system factors which are not explicated in the planning documents.

For our final test, we used the AFQT.WK1 spreadsheet. We entered data for the 63W as shown in Table 47. Our prediction for the AFQT score associated for the 63W is 42. The actual mean AFQT score for this MOS is 48. The RIT-TOM estimate is somewhat lower than the actual score. This difference can be attributed to the fact that the equation that was used does not account for 100 percent of the variance associated with mean AFQT scores. However, the equation's predictions are close.

We have found that in general, our estimates for the MPT values using RIT-TOM are more accurate than our estimates for task times. This is due to the greater number of MPT-related data points we had compared to task time data. Larger amounts of dependent measure data means greater likelihood of prediction capabilities of the utilized multiple regression equation.

Please note, this tool will require re-development once an appropriate data set upon which to base it can be developed. Until then, this tool is best used to demonstrate a potential capability, not a true one.

RELATIONSHIP OF EFFORT TO HARDMAN III

We see this effort as being related to HARDMAN III in three ways. First, the elemental factors selected to represent metafactors in our analyses were derived from the models appearing in the conceptual documents used to define and design the HARDMAN III tools. Thus there is a direct tie back from our analyses with regard to the actual impact of some of the MPT factors appearing in HARDMAN III tools and models and actual maintenance performance. It is important to know these relationships in order to assess the relative importance of a factor upon maintenance and then judge its importance in the context of the model in which it appears. For example, if it is determined via multiple regression analysis that AFQT scores are not predictive of annual maintenance manhours, then it could be removed from models in which this relationship has been included.

Second, the hierarchical relationship between metafactors and elemental factors developed during Phase 1 of this effort (and appearing in Appendix C) can be viewed as an organizing structure for the factors in HARDMAN III in terms of their temporal impact during the acquisition process as depicted by the Driver Factor Model. The Driver Factor Model, since it supplied the organizing metafactors, can be a framework with which one can determine the appropriate timing for use of the HARDMAN III tools and the questions on which to focus at that point in the process. For example, it would be appropriate to make estimations concerning maintenance concept very early in the acquisition process (i.e., for the O&O Plan). Elemental factors to be considered as reflective of the maintenance concept include the number of levels of maintenance. This elemental factor appears in MANCAP2 and is implied by some of the elemental factors in M-CON, such as numbers of maintenance manhours for each maintenance level. Thus, we have both some indication of the tool to use, M-CON, and the timeframe for which it is most appropriate for investigating early questions concerning the impact of the selected maintenance concept.

Finally, in this effort we strove to ensure that the data used in our analyses were either complementary to, or the same as, data used in HARDMAN III analyses. Since we were using elemental factors drawn primarily from documents concerning the HARDMAN III tools, we felt confident in the congruence of the data and factors we used to the HARDMAN III data and factors. Additionally, we selected as the dependent measures for our analyses, and to include in RIT-TOM, variables whose values were identified by personnel working on HARDMAN III tools as useful items which they, in turn, could input into their models.

LESSONS LEARNED

During the performance of this effort, we discovered three issues which greatly impacted the results of the project. Each of these issues will be discussed the following paragraphs with recommendations for alleviating the problems associated with these issues.

Data Issues

As indicated earlier, we identified several inadequacies in the data available for us to perform our analyses. The difficulties that exist differ for the planning data we were collecting and the SDC, or actual maintenance, data that were available. We feel that it is important to focus on the problems with the data for the following reason. In our analysis of potential methods for use in this effort, we determined that of the five methods examined, three would require the same types of data. These three methods were simulation, neural networks, and multiple regression. These three approaches are also the primary ones employed in other MANPRINT efforts, such as HARDMAN III. Therefore, since we had difficulties with data for our MANPRINT effort, it is very likely that other MANPRINT projects will experience similar difficulties with regard to the validity and useability of their results.

Planning Data

When we began our data collection effort, we had the impression that planning and requirements documents such as the O & O Plan, the ROC, BOIP, QQPRI, and SMMP would be available for each of our initial 30 target systems. In other words, we wanted to collect the documents containing system and MPT data that would impact maintenance burden determination during the acquisition process as described in Evans and Roth (1988). However, we determined early during data collection that for some of our systems, no planning or requirements documents were ever developed. For other target systems, only some of the documents we needed were available, and so our Points of Contact (POCs) sent whatever was handy. What we had at the end of this portion of our data collection were sets of documents for a subset of our target systems, but for no two systems did we have all the documents we had requested, and often we had documents we did not request.

One major reason for this inability to access complete sets of planning documents for the target systems was that there is no designated repository for planning documents. What we recovered from our POCs were whatever documents they were able to track down. Since we were requesting documents from the proponent schools, Combat Developers, and Program Offices, one would assume that some individual or office involved with the development and/or fielding of a system would have the planning and requirements documents

associated with the system, even after fielding. We found this not to be the case at all.

In addition to the unavailability of documents, we discovered a lack of comparability among same-type documents with regard to content. Although there were times in which the same types of data items were called out, they would differ in level of detail or methods of expression. For example, mean time to repair might be specified in one ROC as a single value representing all types of maintenance actions, while in the ROC for another system, mean time to repair would be expressed as several values, i.e., one value for preventive maintenance and another for corrective actions. Such discrepancies made comparisons among systems difficult to do accurately and without requiring extensive data manipulation and assumptions.

There were also cases in which documents for a single system would reflect different values for same type data items, depending on the document and its temporal relationship with regard to the acquisition process. For example, we found cases in which the list of MOSs expected to work on the system would be initially determined at some early point in the process, only to be revised at fielding or later. What this lack of congruity among system documents meant was that since we did not have complete document sets, we could not control for the time point at which certain decisions were made with regard to values for system and MPT factors. For example, we had several different types of documents for our systems in which data concerning MOS requirements are listed, but we did not have the exact same documents containing this information for all of the target systems. Rather, for different systems, we have documents containing these data issued at differ points in the acquisition process. We can assume that the decisions concerning MOSs made early in the process are driven by some different factors than those MOS-related decisions made later in the process. Therefore it is questionable whether the data from the two groups really should be used to represent the same factor in the analysis.

One other major difficulty we had with acquiring planning data was the fact that the data base management systems in which much of the data reside are in flux. For example, we accessed the MANPRINT data base maintained by MRSA to retrieve LSAR task data. (We had been informed by a POC at the Logistics Center that the MANPRINT data base was our only source for these data.) However, when we accessed the MANPRINT data base, we discovered that MRSA was still in the process of imputing data into the data base and that LSAR task data existed for only three of our target systems (the M1A1, the M2A1, and the UH-60A). We had to rely on MAC charts (which are developed from LSAR task data) to supply the remainder of our data on pre-fielding estimates for task performance times.

We had a similar problem to the one we had with the MANPRINT data base with the CROSSWALK and FOOTPRINT data bases supported by the Training and Performance Data Center (TPDC) and supplied to us by USAPIC. The CROSSWALK data base contains lists of MOSs categorized by systems to which they are appropriate. The FOOTPRINT data base contains MPT data by MOS. To determine MOS data for personnel working on a system, one can identify the appropriate MOSs from reports from the CROSSWALK data base, and then examine the reports of the FOOTPRINT data base for those MOSs. However, both data bases are

updated on a continual basis, and so a CROSSWALK report issued in one month may be different from one issued the following month. Our difficulty arose from requesting FOOTPRINT reports for aviation MOSs which had been called out both in the planning documents for our target aviation systems and on the CROSSWALK reports we had. After failure to retrieve the needed FOOTPRINT reports, we discovered that the Army was in the process of replacing or reassigning several aviation MOSs to new MOS designators (from 35* to 67*). The new MOS designators appeared in the FOOTPRINT data base, but the data associated with the old MOSs had not been transferred to the new MOSs and had not been retained on the data base under the old designator. Therefore we were unable to acquire MPT data for these personnel.

These difficulties in acquiring data and in the quality of the data which we were able to acquire resulted in the need to omit data for some cases. In other cases, we were attempted to extrapolate from sources we had to fill in missing data. For example, we would use the same-type data for a similar system to represent the target system or the same-type data from one MOS to represent a similarly-tasked MOS. To make these extrapolations, we had to make certain assumptions concerning the similarities among systems and MOSs. We are not at all certain to the true validity of the assumptions we were forced to use in order to generate a data set of suitable size for analysis. Just the fact that we had to manipulate the data representing our independent factors means that the results of our analysis are questionable, although the method employed was appropriate to the questions which were the focus of the research.

Dependent Measure Data

We found several problems with the SDC data we used for our dependent measures, as well. First, the commodity commands do not monitor task performance accuracy. Accuracy is an important component of performance. On many types of tasks one can observe a trade-off between task speed and accuracy, in that as the performer quickens his pace at the task, the accuracy of performance is reduced. (However, once task performance becomes automatic, then forcing the performer to act more slowly may not result in more accurate results, because it changes the nature of the task by forcing the person to more closely mediate his behavior. See Shiffrin and Schneider's 1977 work for more on the difference between automatic and controlled behavior.)

Second, we found similar comparability problems with the SDC data generated by the different commodity commands as we found for planning documents across systems. The different commodity commands collect similar, but not necessarily identical types of data. For example, the Aviation Systems Command (AVSCOM) collects performance task data by the types of tasks appearing in the MACs for each MOS working on the system. Missile Command (MICOM), on the other hand, collects task time data in terms of preventive or corrective tasks, and cannot easily, if at all, break the tasks out by type of task at a more detailed level. In some cases, we had times for MAC-like tasks, but only for each level of maintenance and not as we needed, which was level of maintenance by MOS. Thus we had to either leave blanks for missing

data or, in the case of times for correct tasks at different maintenance levels which were not divided out by MOS, we used the same task times for all MOS at the same maintenance level for the system.

Another difficulty with the task time data available from SDC sources is that it is unclear as to what is actually being measured as task performance times for SDC. There was some indication in documents supplied to us by MRSA defining the collected data items for several of our target systems as to the components for task time determination. These documents indicated that recorded task times reflected actual hands-on maintenance actions only, and did not include time spent reviewing procedural steps, locating assistance, or waiting for parts. Thus the task time data reflected only the best performance of the maintainers, not the actual total time expended for each maintenance activity.

In order for MANPRINT analyses to be successful, we must have access to task time data which reflects things such as the time spent examining documents or requesting help. Without these data we cannot draw an accurate picture of the relationship between task performance as reflected by time to perform and such factors as length of training and personnel characteristics.

A fourth difficulty with SDC data is that it is collected for only a portion of a system's life, and not across the whole life cycle. Therefore we cannot assess the interaction between system aging and MPT factors as they impact maintenance performance. It is very possible that we would find differences with regard to MPT requirements for a newly fielded system versus one that is near the end of its operational life. It may be that older systems are more likely to require frequent or unusual repairs than new systems. If personnel are not familiar or practiced with these tasks due to their rarity, it may impact their performance of them. It seems that it would be important for the Army to be able to plan its MPT requirements for systems throughout their life cycles.

An additional problem we identified during this effort was with regard to data concerning operational availability (A_o), one of the dependent measures we considered using. As described earlier, we had little or no indication of the methods by which elements for the equation for calculating A_o were derived. We could assume that equation elements such as "operating time during a given calendar period" are based on the same calendar periods. However, some of the data we did have indicated that was a fallacious assumption. Unfortunately, A_o is only meaningful across systems if all measurements refer to the same, or reasonably similar, time periods. (For example, a new system whose availability is calculated based on the initial five months after fielding may have a higher availability than an older system whose availability is measured over 12 months. However, if the availabilities for both systems are calculated over the longer length of time, the availability for the new system may decrease as it ages, making potentially more comparable to the older one.)

For some elements, we could identify the method whereby the A_o equation elements were generated, but the procedures or data used by the different commodity commands did not result in comparable data. For example, task times for performing maintenance are necessary to calculate the "total corrective

maintenance downtime" for a system, another element of the A_0 equation. Given our experience with the SDC data, we know that the various commodity commands do not collect maintenance times for the same categories of tasks. ne task times they do collect, however, are used to calculate operational availability. Since the commodity commands use different constellations of task types to supply data for their calculations, the results of these calculations are not directly comparable, unless one can determine which tasks were used and which were not, and thus compensate for the differences.

A final problem with the SDC data is the inaccessibility of some of the available data. We initially made our data requests to MRSA to use their Core Data Element (CDE) data base which had computable data items across systems supported by the different commodity commands. However, at the beginning of 1990, during the time frame we had set for gathering actual maintenance data, MRSA's CDE program was cancelled and the data base information made unavailable. This occurrence meant that we had to interact with the individual commodity commands to access their specific data bases and attempt to identify core data element type information ourselves.

Methods for Correcting Data Problems

For the type of project we undertook, having valid and appropriate data is one of the most important considerations in the success of the effort. Given the difficulties we encountered with data retrieval and data utility, we felt that it would be appropriate for us to suggest means for ameliorating the types of difficulties we encountered.

To overcome the difficulty of locating system planning and requirements documents, the Army might establish a central repository for these types of items for all systems for which they are generated. These documents would not necessarily have to be stored as paper documents, but could be maintained as microfiche. One potential location for this repository could be the Pentagon Library. The Pentagon Library has facilities for maintaining both classified and unclassified materials.

An additional method for correcting problems we identified in the planning data is to develop more detailed procedures for document preparation to be used by everyone who constructs these types of items. Although guidance for document development already exists in TRADOC/DARCOM PAM 70-2 (1980), it appears to be insufficient to ensure that comparable data items appear in same-type documents pertaining to different systems. For example, mean times to repair appearing in the ROCs should be indicated at each level of maintenance, rather than sometimes being expressed for all levels for some systems and for individual levels for other systems.

It would also be useful if planning and requirements documents prepared later in the acquisition process included some indication of the items modified from previously prepared documents, and the extent of the change. For example, say the ROC specifies a particular mean time to perform maintenance at the unit level and then a decision is made to increase this time,

with the new value appearing in the Material Fielding Plan for the system. The Material Fielding Plan should indicate the new value, the old value and its source, and the reason for modification. In this way, researchers could better ensure that the data they are using are generated at the same point in the acquisition process for all systems under examination. It would also allow researchers the option to look at the ways in which intermediate decisions can cause the re-examination and modification of previously made MPT decisions.

With regard to SDC data, we can make several suggestions for assuring the presence of data useful for MANPRINT analyses. First of all, if the Army were to more completely standardize across all commodity commands both the procedures whereby the data are collected and the data items themselves, this would greatly alleviate the problem. This standardization would ensure that data across systems can be compared.

In addition to standardization of data collection procedures and elements, the SDC data collection process should also include the addition of new data elements. For example, actual maintenance performance times that include the time spent by the maintainer examining documentation or receiving advice from others should be measured. Additionally, performance accuracy for each maintenance task performed should be recorded. This latter measure would mean monitoring component performance by both the specific maintainer and its next occurrence of failure or, for components sent to the next higher level of maintenance, whether or not the component retested operational (RETest OKay, or RETOK).

Although modifying data collection procedures as extensively as described would be a large effort, there is a model for such data collection which the Army could examine. We recommend that the Army examine the methods for collecting maintenance data employed by the U. S. Air Force (USAF).

USAF's maintenance organization and data collecting methods are described in detail in Multiple Command Regulation (MCR) 66-5. According to MCR 66-5, maintenance records are kept on all weapons systems and their individual components by all personnel who have maintained said systems or components. This information is maintained on each USAF Base for the base's assets in a computer system whose software is not base-specific, but Air Force-wide. This information includes accuracy data in the form of system/subsystem/component failures after repair or RETOKs. It also keeps track of all maintainers who have worked on the item. Thus, repair accuracy can be traced back to the original maintainer.

In addition to supplying maintenance performance accuracy data, USAF's requirements for recording time to perform maintenance is by type of maintenance action or malfunction code, and it includes all time spent by the maintainer until the item is fixed or sent to the next level and a replacement part is ordered. At that point, the larger unit (system or subsystem) is relegated to await parts status and the end time for the job is recorded. Time to repair starts again in the form of a new job start time or a re-opened job with an associated start time when the part arrives. Thus the time spent waiting for parts can be easily computed by subtracting the original job stop time from the new or re-opened job start time for the item under repair.

(However, in cases in which the part is available and arrives from Supply quickly, the total job time includes the time spent waiting for the part. This situation usually only occurs when it is imperative that the aircraft be available for a mission.)

It should be noted that the time to perform includes all the time spent by the maintainer examining documents and asking for help. That is because an Air Force maintainer is required to look at his technical orders while performing maintenance tasks. (The Air Force technical manuals are actually orders, as given by a superior, and must be referred to while performing a maintenance task.)

In his paperwork for a maintenance job, the maintainer indicates the type of job or malfunction, his job start time, his completion time, and the outcome of the job (i.e., was the repair completed? Was the part sent to the Intermediate level? Was a replacement part available or was it back ordered? Is the asset now mission capable?) Such times and other information, in conjunction with the task performance data described earlier, can be used as indicative of actual maintenance performance which could be impacted by better quality personnel, training, or documentation.

Methodological Issues

Drawbacks of Multiple Regression

Although we used the analysis method we felt was the most appropriate for the goals of the project (see the Project Description section in which we discuss how we determined this), we found there were also drawbacks to this method. Many of these problems were the result of the data we had collected, or lack thereof.

The first difficulty with our selected method of data analysis was the fact that some of our independent factors were highly correlated. (For example, we found that predicted assignment and number of personnel authorized had an inter-correlation of .98.) This led to the problem of multi-collinearity. Multi-collinearity means that of the set of independent factors, several are really indicative of the same higher-order factor, and thus the weight for each independent factor which is highly correlated with the others will be impacted by the weights assigned to the other factors. This means the Beta weights for the inter-correlated factors may not be truly reflective of their predictive relationship to the dependent measure with regard to each other. To avoid this problem, one should select factors which are orthogonal to each other.

There is a benefit to the multi-collinearity problem, however. Having such a problem means one has the ability to define equations in which highly inter-correlated factors can substitute for each other with the addition of a correction factor. This suggests the possibility of multiple trade-off tools, based on availability of data for use with a tool.

One could expect the multi-collinearity problem to surface in our situation, since we were using one or more elemental factors to stand for each metafactor. However, some of the high correlations we found between factors were unexpected. Usually high inter-correlations indicate the need to identify some higher-order factor through a process such as factor analysis. However, in our case, these high inter-correlations may have been more spurious than real, due to the extent of data we were missing. Spurious, or not, however, the problem of multi-collinearity still exists in our results.

Missing data points also resulted in forcing some of the independent factors out of tolerance during analysis. This meant that these particular factors were dropped from the analysis by the program. If we had not had any missing data, we would have not had this situation, and all factors would have been examined for inclusion in the equations.

A third problem with the selected analysis method was that we did not have cases representing all combinations of categorical elemental factors. In other words, we did not have a fully crossed design. This difficulty arose from the fact that we had only nine systems and limited types of MOSs for analysis, and therefore did not have all potential cases. The results of this problem is that we are unable to generalize our findings to types of cases for which we had no data thus limiting the usefulness of our analyses and the tool based upon them.

The lack of data also meant that we could not assume that the data represented a normal distribution. This lack of normality meant that some of the developed equations can result in impossible values when used for prediction.

There is one final negative aspect of using the multiple regression method for analysis. In cases in which we did not produce equations that accounted for 100 percent of the variance, we cannot be assured of being able to correctly predict the dependent measure given values for the elemental factors in the equation.

Required Methodological Changes

To summarize the drawbacks of our selected analytical method, we cannot be certain of the predictive capabilities of the equations we have developed due to: (1) the quantity of missing data, (2) the lack of a fully crossed design, (3) multi-collinearity, and (4) the inability to account for 100 percent of the variance in the dependent measures. There are some obvious ways to overcome these difficulties, if the work is re-done in the future.

First, we would need to reduce the number of missing data items. This could be done if the Army implemented changes to the document production and SDC data collection procedures described earlier.

Second, if the Army collected SDC data on all material systems continuously, rather than a few select systems over a few years, data would be available for developing a more complete set of cases. This would mean that the equations, and tool resulting from them, would be more generalizable to cases not used in development.

Third, once we are able to resolve the data quality and quantity problems, we can begin to address the multi-collinearity issue. To do this, we would need to perform a factor analysis and extract out the higher-order factors represented in the data, rather than relying on the existing model to define them. Once we have identified higher-order factors, we can then select the component elemental factor which best represents that higher-order factor or use a composite factor based on a set of elemental factors. It would be nice if the higher-order factors mapped directly onto the metafactors identified in this project, but it could be that the metafactors from the Driver Factor Model are not truly supported by the data or the potential elemental factors, but that others are.

Factor Selection Issues

The third area in which we identified issues was factor selection. By necessity, we were selective, and did not include all possible elemental factors, or even all metafactors, for examination. This selective behavior could have resulted in us potentially selecting inappropriate factors for study. For some of the dependent measures, it is obvious that there may have been other more predictive elemental factors than we ones we used. However, in the cases in which the equations predicted 90-100 percent of the variance, we might have developed alternative equations, but not any that were more predictive.

To alleviate the difficulties associated with the method we employed to select elemental factors to represent metafactors, we could have examined potential elemental factors in relation to its specific metafactor to identify the factor which best represented the metafactor. Alternatively we could have developed a composite factor prior to analysis via factor analysis and then used the composite factor.

Conclusions

It should be pointed out that this project was undertaken as an exploratory effort. We undertook to develop a method for approaching MANPRINT issues related to maintenance. We also attempted to develop a trade-off tool for exploring this issue. It is very debatable as to the utility of the current version of the tool, given the inaccurate, and occasionally impossible, values it generates. However, we feel that our experience has allowed us to pin-point many of the problems that must be overcome in order to perform useful MANPRINT analyses and to arrive at a method which could be useable at

some future point after the difficulties described within this report have been ameliorated.

FUTURE WORK

There are several promising areas for future work implied by this effort in maintenance MANPRINT. First, there is a need to design procedures to ensure that better quality data, in sufficient quantity, are available for all MANPRINT analysis efforts. We do not think that the difficulties with data experienced by this project are isolated incidents, since we were drawing on the same data available to all other MANPRINT efforts. Other MANPRINT efforts are likely to suffer the same negative impacts resulting from data quantity and quality, as the project described in this report for reasons mentioned in the previous section.

Second, once the data quality and quantity problems have been addressed, it would be useful to re-examine the elemental factors from this study and, using factor analysis, develop composite factors for inclusion in multiple regression analyses of the type described in this report. In this way, we would be better able to identify actual metafactors supported by the data for the elemental factors, rather than relying on a conceptual model containing metafactors for which we have assumed that the elemental factors represent. With this type of analysis, we might discover that there is no mapping between the higher order factors described by the data and the conceptual model. However, we might find that the Driver Factor Model metafactors are truly represented by the elemental factors.

After better data become available and the precise relationship among the elemental factors and the metafactors have been established, it would be useful to re-run analyses performed during this project using composite factors derived through factor analyses (one for each dependent measure), as described above. The results of such analyses could be used to update RIT-TOM. At that point RIT-TOM could potentially be a useful tool with which to perform sensitivity analyses and trade-off studies. The number of spread-sheets associated with RIT-TOM could be expanded and embedded in an expert system shell which would aid the user in spreadsheet selection and data entry.

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APPENDIX A

ACRONYM LIST

APPENDIX A

ACRONYM LIST

The following list consists of the acronyms, and their meanings, used throughout this report.

$A_{MANPRINT}$	MANPRINT Availability
Ao	Operational Availability
AAPMH	Annual Available Productive Manhours
AAMPMH	Annual Available Maintenance Productive Manhours
AFQT	Armed Forces Qualification Test
AMCCOM	Armament, Munitions, and Chemical Command
AMH	Annual Maintenance Manhours
AMMDB	Army MARC Maintenance Data Base
AMMH	Annual Maintenance Manhours
APC	Armored Personnel Carrier
APT	Aptitude
ARI	Army Research Institute
AVIM	Aviation Intermediate Maintenance
AVSCOM	Aviation Systems Command
AVUM	Aviation Unit Maintenance
BIT	Built-in Test
BITE	Built-in-Test Equipment
BOIP	Basis of Issue Plan
CALS	Computer-Assisted Logistics Support
CDE	Core Data Element
CUCV	Commercial Utility Cargo Vehicle
DBMS	Database Management System

DPAMMH	Direct Productive Annual Maintenance Manhours
ECM	Electronic Countermeasures
EMP	Electromagnetic Pulse
FIN	The minimum value of the F statistic needed to be entered into the equation
HARDMAN	HARDware versus MANpower Analysis
HARDMAN III	A set of five software products to support HARDMAN
HFE	Human Factors Engineering
HMMWV	High Maneuverability Mobile Wheeled Vehicle
IDS	Intermediate Direct Support
IGS	Intermediate General Support
JEMNS	Joint Element Mission Need Statement
JSOR	Joint Service Operations Requirements
KSA	Knowledge, Skills, and Abilities
LOA	Letter of Approval
LSA	Logistic Support Analysis
LSAR	Logistical Support Analysis Record
M-CON	Manpower Constraints Estimation Aid
MAC	Maintenance Allocation Chart
MANCAP 2	Manpower Capabilities (Software product for manpower requirements analysis)
MANPRINT	MANPoweR INTegration
MAN-SEVAL	Manpower Determination Aid
MAP	Materiel Acquisition Process
MARC	Manpower Requirements Criteria
MCR	Multiple Command Regulation
MICOM	Missile Command

MOS	Military Occupation Specialty(ies)
MPT	Manpower, Personnel, and Training
MRSA	Materials Readiness Support Activity
MTBF	Mean Time Between Failure
MTTR	Mean Time To Repair
O & O	Operational and Organizational
O & O PLAN	Operational and Organizational Plan
OPTEMPO	Operational Tempo
OT	Operating Time During a Given Calendar Time Period
P-CON	Personnel Constraints Estimation Aid
PERS-EVAL	Personnel Requirements Estimation Aid
PIN	Probability of F-to-enter into the equation
POC	Point of Contact
POI	Plans of Instruction
POL	Petroleum, Oils, Lubricants, Expendables, or Consumable items
QQPRI	Qualitative and Quantitative Personnel Requirement Information
RETOK	Re-Test Okay
RIT-TOM	Requirements Integration Trade-Off Tool for Maintenance
ROC	Required Operational Capabilities
SDC	Sample Data Collection Database
SMMP	System MANPRINT Management Plan
SPARC	System Performance Requirements Estimation Aid
ST	Standby Time
STRAP	System Training Plan

TACOM	Tank-Automotive Command
TALDT	Total Administrative Logistics Down Time
T-CON	Training Constraints Estimation Aid
TCM	Total Corrective Maintenance Time
TMDE	Test, Measurement, and Diagnostic Equipment
TOE	Table of Organization and Equipment
TPDC	Training and Performance Data Center
TPM	Total Preventative Maintenance Down Time
TPR	Task Performance Requirements
TTHS	Trainees, Transients, Holdees, and Students
USAF	United States Air Force
USAPIC	U. S. Army Personnel Integration Command
Z Scores	Standardized Scores

APPENDIX B

LIST OF METAFACTORS SELECTED IN PHASE 1

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LIST OF METAFACTORS SELECTED IN PHASE 1

The selected metafactors (or metafactor groups) with their selected component elemental factors are as follows:

Metafactors: BOIP, MOS

Elemental Factors: Military Occupation Specialty (MOS) main duty type
Number of maintainers of MOS duty type
Total MOS Requirements

(These metafactors indicate the types of personnel who will be performing system maintenance tasks. For analysis, this information comes from the system SMMP or BOIP.)

Metafactors: Operational and Organizational (O & O) Plan, System (System type)

Elemental Factors: System Description
System Function
System
System use conditions

(This metafactor represents the system and its mission, both of which define constraints to the performance of maintenance. For analysis, this information comes from the System O & O Plan.)

Metafactor: Eaches

Elemental Factor: # Systems to field

(This metafactor indicates the number of systems to be fielded, thus impacting total maintenance requirements. This information is found in various planning documents.)

Metafactor: Test, Measurement, and Diagnostic Equipment/Built-In Tests/Built-In Test Equipment (TMDE/BIT/BITE) capability

Elemental Factors:
- Number of TMDE/BIT/BITE supports per system
- Complexity of use
- Failure rate of TMDE/BIT/BITE when used
- Mean time to find failure using TMDE/BIT/BITE

(This metafactor reflects the availability and capability of sy..-m troubleshooting aids. Information concerning TMDE/BIT/BITE can be found in the system Required Operational Capabilities [ROC] document.)

Metafactors: Task, Maintenance Tasks

Elemental Factors:
- Test
- Repair
- Replace
- Inspection
- Service
- Adjust
- Overhaul

(These metafactors address the maintenance tasks to be performed, as reflected in MAC charts, for the system or subsystem by the MOS type. For analysis, this information for the elemental factors comes from the coordination of system MAC charts with MOS task lists available from the Training and Performance Data Center [TPDC] or in the System MANPRINT Master Plan [SMMP]).

Metafactor: Maintenance Concept

Elemental Factor: # Levels of Maintenance for system

(This metafactor represents the decision as to the organization of the maintenance function. For analysis, information can be found in system O & O Plans.)

Metafactor: Maintenance Profile

Elemental Factors:
- % Task allocation to maintenance level
- Time allocation for task by maintenance level

(This metafactor represents the interaction of maintenance concept with maintenance tasks. For analytic purposes, this information can be found in system Maintenance Allocation Charts [MACs].)

Metafactors: System use rates, Operational Tempo (OPTEMPO)

Elemental Factors: # Missions/year
Miles/year

(This is the OPTEMPO for the system. It can be found in the system O & O Plan or the ROC.)

Metafactor: System Maintenance Characteristics

Elemental Factors: Mean Time Between Failure (MTBF)
Mean Time To Repair (MTTR)
Direct Productive Annual Maintenance ManHours (DPAMMH) by MOS and Maintenance Level

(This metafactor encapsulates the expected or desired results of the technological opportunities and design issues as they interact with the MPT factors. For the analysis, the data for the subsumed factors MTBF and MTTR appear in the system Logistical Support Analysis Record or ROC.)

Metafactor: Manpower Pool Characteristics, Personnel to be Trained

Elemental Factors: Mean Armed Forces Qualification Test (AFQT) score by MOS
Civilian Education Level by MOS
Mean Prerequisite Test Entry Score by MOS

(The selected elemental factors for manpower pool characteristics and personnel to be trained are those that are likely to have some predictive power for maintenance burden or time to repair, due to the usually found relationship between selection test scores, experience, and job performance. These data can be found for our analysis in TPDC Footprint reports and system SMMPs.)

Metafactor: Training System

Elemental Factors: % Tasks trained at the institution by MOS
% Tasks trained at the Unit by MOS
Length of Training by MOS

(The training system metafactor is represented by elemental factors which are likely to have an impact on the variate, task performance times. These factors are indicative of the amount and location of training received by personnel. Data for these elemental factors can be found in system SMMPs and Plans of Instruction.)

Metafactor: Availability

Elemental Factors: Authorized availability by MOS and system
Projected availability by MOS and system
Retention rate by MOS and system
Operating strength by MOS and system

(This metafactor reflects the expectations of manpower availability in the form of authorized manpower and projected availability. For analysis, these data can be found in system SMMPs and TPDC Footprint reports.)

A factor confidence value will be developed for each factor included in the Phase 2 analysis. This confidence value will be based on the number of systems which contributed actual data to each elemental factor (as opposed to data extrapolated from similar systems) during the analysis. Also, the metafactors will be assigned a standard metric. This metric will be based on their rank order of importance. Factor importance will be directly related to the amount of variance accounted for by the metafactor as reflected by the variance accounted for by its elemental factors.

APPENDIX C

RELATIONSHIPS AMONG MAINTENANCE MANPRINT FACTORS

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RELATIONSHIPS AMONG MAINTENANCE MANPRINT FACTORS

Appendix C presents all unique maintenance-relevant factors found in HARDMAN III products and classifies them by the Evans & Roth Driver Factor Model factors. Each factor is identified by its name, the models in which it appears, and the reference(s) in which the factor was found. When the listed reference is "Concept Document" the reference is to the following documents for each HARDMAN III product:

a. SPARC (Dahl, et al., 1987)

b. M-CON (O'Brien, 1987a)

c. P-CON (O'Brien, 1987b)

d. T-CON (Roth, et al., 1987)

e. MAN-SEVAL (Archer, et al., 1987)

f. PERS-EVAL (O'Brien & Dahl, 1987)

g. Briefing materials on MANCAP 2 - (Dynamics Research Corporation & Micro Analysis and Design, 1989).

When the reference lists "Data Dictionary" it refers to the HARDMAN III CALS MPT2 Data Element Dictionary (O'Brien, 1989).

RELATIONSHIPS AMONG MAINTENANCE MANPRINT FACTORS

Driver Factor Model Factors: AVAILABILITY

Factor: ATTRITION
Model(s): P-CON
Reference: Concept Document

Factor: MIGRATION FROM MOS
Model(s): P-CON
Reference: Concept Document

Factor: PROMOTION RATES
Model(s): P-CON
Reference: Concept Document

Factor: RETENTION
Model(s): P-CON
Reference: Concept Document

Factor: CURRENT OPERATING STRENGTH
Model(s): M-CON
Reference: Concept Document

Factor: CURRENT AUTHORIZATIONS
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: BOIP, MOSs, EXISTING MOS DATA, ORGANIZATIONAL STRUCTURE

Factor: REPLACEMENT SYSTEM MOS REQUIREMENTS BY UNIT
Model(s): M-CON
Reference: Concept Document

Factor: MOS/GRADE ASSIGNED TO NEW SYSTEM'S TASKS
Model(s): PERS-EVAL
Reference: Concept Document

Factor: MOS/GRADE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: SYSTEM MOS REQUIREMENTS BY UNIT
Model(s): M-CON
Reference: Concept Document

Factor: MOS/GRADES AUTHORIZATIONS
Model(s): M-CON
Reference: Concept Document

Factor: MOS
Model(s): M-CON, T-CON, P-CON, MANCAP 2
Reference: Concept Document
Factor: NEW MOS FACTORS CHECKLIST
Model(s): M-CON
Reference: Concept Document

Factor: TOTAL MOS REQUIREMENTS
Model(s): M-CON
Reference: Concept Document

Factor: MOSs BY MAJOR SYSTEM
Model(s): M-CON
Reference: Concept Document

Factor: LIKELY MOSs
Model(s): M-CON
Reference: Concept Document

Factor: LIKELY SOURCE MOSs FOR NEW SYSTEM
Model(s): M-CON
Reference: Concept Document

Factor: NUMBER OF MAINTAINERS OF MOS/LEVEL
Model(s): MANCAP 2
Reference: Concept Document

Factor: SOURCE MOSs FOR NEW MOS
Model(s): M-CON
Reference: Concept Document

Factor: REVISED MOS/GRADE AUTHORIZATION
Model(s): M-CON
Reference: Concept Document

Factor: REVISED MOS ASSIGNMENTS
Model(s): M-CON
Reference: Concept Document

Factor: REVISED SYSTEM MOS REQUIREMENTS BY UNIT
Model(s): M-CON
Reference: Concept Document

Factor: REVISED TOTAL MOS REQUIREMENTS
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: BOIP, SUMMATIVE MANPOWER REQUIREMENTS, MANPOWER, TTHS FACTORS DATA

Factor: AUTHORIZATION RATIO
Model(s): M-CON
Reference: Concept Document

Factor: OPERATING STRENGTH RATIO
Model(s): M-CON
Reference: Concept Document

Factor: EXPECTED NUMBER OF PERSONNEL REQUIRED FOR TASK
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: CURRENT TOTAL REQUIREMENTS
Model(s): M-CON
Reference: Concept Document

Factor: ADJUSTED AUTHORIZATIONS
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: BOIP, SUMMATIVE MANPOWER REQUIREMENTS, NUMBER OF PEOPLE IN MANPOWER POOL, AVAILABILITY

Factor: ADJUSTED MANPOWER
Model(s): M-CON
Reference: Concept Document

Factor: ADJUSTED REQUIREMENTS
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: BOIP, SYSTEM, NUMBER OF SYSTEMS, EACHES

Factor: NUMBER OF REPLACEMENT SYSTEMS
Model(s): M-CON
Reference: Concept Document

Factor: NUMBER OF SYSTEMS/EACHES
Model(s): MANCAP 2
Reference: Concept Document

Factor: NUMBER OF LOW LEVEL UNITS WITH OLD SYSTEM
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: BOIP, TOE, NUMBER OF SYSTEMS PER UNIT

Factor: NUMBER OF LOW LEVEL UNITS TO RECEIVE NEW SYSTEM
Model(s): M-CON
Reference: Concept Document

Factor: NUMBER OF NEW SYSTEMS PER UNIT
Model(s): M-CON
Reference: Concept Document

Factor: UNITS TO GET NEW SYSTEMS
Model(s): M-CON
Reference: Concept Document

Factor: TYPE OF UNITS TO GET NEW SYSTEM
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: LEVELS OF MAINTENANCE, O & O CONCEPT DOCUMENT, MAINTENANCE CONCEPT DOCUMENT, ORGANIZATIONAL CONCEPT DOCUMENTS

Factor: LEVELS OF MAINTENANCE
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: LSA, TASK

Factor: MEAN TASK ACCURACY FOR BASELINE EQUIPMENT
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK ACCURACY STANDARD DEVIATION FOR BASELINE EQUIPMENT
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Driver Factor Model Factors: LSA, MAC, SYSTEM MAINTENANCE CHARACTERISTICS, TASK, SERVICE AND REPAIR TASKS, FAULT ISOLATION TASKS, MAINTENANCE TASKS, TASK PERFORMANCE REQUIREMENTS (TPR)

Factor: MEAN TIME TO REPAIR SUBSYSTEM
Model(s): T-CON
Reference: Concept Document, Data Dictionary

Factor: STANDARD DEVIATION OF TIME TO REPAIR SUBSYSTEM
Model(s): T-CON
Reference: Concept Document, Data Dictionary

Factor: MEAN TIME TO TROUBLESHOOT SUBSYSTEM
Model(s): T-CON
Reference: Concept Document, Data Dictionary

Factor: STANDARD DEVIATION OF TIME TO TROUBLESHOOT SUBSYSTEM
Model(s): T-CON
Reference: Concept Document, Data Dictionary

Factor: EXPECTED MAINTENANCE MANHOURS PER MAINTENANCE ACTION
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: ESTIMATE FOR NEW TASK PERFORMANCE TIME
Model(s): PERS-EVAL
Reference: Concept Document

Factor: EXPECTED PERCENT OF TIME BY TASK FOR MAINTENANCE
Model(s): MAN-SEVAL
Reference: Concept Document, Data Dictionary

Factor: EXPECTED MAINTENANCE MANHOURS PER MAINTENANCE CATEGORY
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: TASK TIME ESTIMATE FOR BASELINE EQUIPMENT
Model(s): PERS-EVAL
Reference: Concept Document

Factor: NUMBER OF PROCEDURAL STEPS FOR TASK COMPLETION
Model(s): PERS-EVAL
Reference: Concept Document

Factor: PREDICTED GENERAL MAINTENANCE STANDARD SCHEDULE
Model(s): P-CON
Reference: Concept Document

Driver Factor Model Factors: LSA, MAC, SYSTEM MAINTENANCE CHARACTERISTICS, MAINTENANCE BURDEN, MOSs, MAINTENANCE PROFILE, TASK ALLOCATION STRATEGY, TASK PERFORMANCE REQUIREMENTS (TPR), TASKS AND LEVELS

Factor: EXPECTED MAINTENANCE MANHOURS BY MOS & SKILL LEVEL
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: EXPECTED MAINTENANCE MANHOURS BY MOS & TASK
Model(s): MANCAP 2
Reference: Concept Document

Factor: AAPMH - IG
Model(s): M-CON
Reference: Concept Document

Factor: AMMH BY MOS & PAYGRADE - IG
Model(s): M-CON
Reference: Concept Document

Factor: AAMPMH - ID
Model(s): M-CON
Reference: Concept Document

Factor: AAMPMH - O
Model(s): M-CON
Reference: Concept Document

Factor: AMMH BY MOS & PAYGRADE - ID
Model(s): M-CON
Reference: Concept Document
Factor: AMMH BY MOS & PAYGRADE - O
Model(s): M-CON
Reference: Concept Document

Factor: DPAMMH PER EQUIP ITEM - ID
Model(s): M-CON
Reference: Concept Document

Factor: DPAMMH PER EQUIP ITEM - IG
Model(s): M-CON
Reference: Concept Document

Factor: DPAMMH PER EQUIP ITEM - O
Model(s): M-CON
Reference: Concept Document

Factor: INDIRECT PRODUCTIVITY TIME - ID
Model(s): M-CON
Reference: Concept Document

Factor: INDIRECT PRODUCTIVITY TIME - O
Model(s): M-CON
Reference: Concept Document

Factor: INDIRECT PRODUCTIVITY TIME - IG
Model(s): M-CON
Reference: Concept Document

Factor: MAX DPAMMH
Model(s): M-CON
Reference: Concept Document

Factor: DPAMMH - IG
Model(s): M-CON
Reference: Concept Document

Factor: DPAMMH - ID
Model(s): M-CON
Reference: Concept Document

Factor: DPAMMH - O
Model(s): M-CON
Reference: Concept Document

Factor: EXPECTED MAINTENANCE MANHOURS PER COMPONENT
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: EXPECTED MAINTENANCE MANHOURS PER FUNCTIONAL SYSTEM
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: EXPECTED MAINTENANCE MANHOURS PER MAINTENANCE ACTION TYPE
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: TIME ALLOTTED TO PERFORM MAINTENANCE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TIME REQUIRED TO PERFORM MAINTENANCE
Model(s): PERS-EVAL
Reference: Concept Document

Factor: DIRECT MAINTENANCE MANHOURS ALLOWED
Model(s): MANCAP 2
Reference: Concept Document

Factor: DURATION OF OUTPUT FOR UNIT MAINTENANCE
Model(s): PERS-EVAL
Reference: Concept Document

Factor: MAXIMUM ALLOWABLE REPAIR TIME
Model(s): MANCAP 2
Reference: Concept Document

Factor: EXPECTED DPAMMH
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: LSA, MAINTENANCE BURDEN, MAC, ORGANIZATIONAL CONCEPTS

Factor: MAINTENANCE ORGANIZATION FOR TASK
Model(s): MAN-SEVAL
Reference: Concept Document

Driver Factor Model Factors: LSA, SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS, SYSTEM MAINTENANCE CHARACTERISTICS, TASK PERFORMANCE REQUIREMENTS (TPR)

Factor: LSAR ESTIMATED MEAN UNITS BETWEEN FAILURE
Model(s): MAN-SEVAL
Reference: Concept Document, Data Dictionary

Factor: LSAR MEAN TIME TO REPAIR
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: LSAR STANDARD DEVIATION OF TIME TO REPAIR
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: TASK MAXIMUM PERFORM TIME
Model(s): SPARC
Reference: Concept Document

Factor: TASK MOST LIKELY PERFORMANCE TIME
Model(s): SPARC
Reference: Concept Document

Driver Factor Model Factors: LSA, SYSTEM

Factor: SUBSYSTEMS FOR MAINTENANCE
Model(s): T-CON
Reference: Concept Document

Factor: COMPONENT DESCRIPTION
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: EQUIPMENT ITEM
Model(s): PERS-EVAL, MANCAP 2
Reference: Concept Document

Factor: SUBSYSTEM ATTRIBUTE
Model(s): T-CON
Reference: Concept Document

Factor: COMPONENT NAME
Model(s): MAN-SEVAL, PERS-EVAL
Reference: Concept Document

Driver Factor Model Factors: LSA, TASK, SERVICE AND REPAIR TASKS, FAULT ISOLATION TASKS, MAINTENANCE TASKS

Factor: PERCENT MEMBERSHIP OF TASK IN TASK TYPE
Model(s): PERS-EVAL
Reference: Concept Document

Factor: NUMBER OF TASK TYPES
Model(s): PERS-EVAL
Reference: Concept Document

Factor: TASK PERFORMANCE PRIORITY
Model(s): PERS-EVAL
Reference: Concept Document

Factor: TASK TIME ESTIMATE GIVEN CONDITION
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TYPE OF EFFECT OF TASK CONDITION
Model(s): PERS-EVAL
Reference: Concept Document

Factor: COMPONENT OPERATIONAL UNITS PER MISSION
Model(s): MAN-SEVAL, PERS-EVAL
Reference: Concept Document

Factor: TASK CATEGORY
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK SEQUENCE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: MEAN TASK ACCURACY
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TASK ACCURACY STANDARD DEVIATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TASK COMPLETION PROBABILITY
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: MAINTENANCE ACTION
Model(s): MAN-SEVAL, MANCAP 2
Reference: Concept Document, Data Dictionary

Driver Factor Model Factors: MAINTENANCE BURDEN, BOIP, MAC, MAINTENANCE ALLOCATION

Factor: INDIRECT MAINTENANCE TIME X MOS & LEVEL
Model(s): MANCAP 2
Reference: Concept Document

Factor: DIRECT MAINTENANCE TIME X MOS & LEVEL
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: MAINTENANCE STRATEGY, TASK ALLOCATION STRATEGY

Factor: CONTACT TEAM USE
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: MAINTENANCE TASKS, MAINTENANCE BURDEN

Factor: MAINTENANCE TASKS
Model(s): MANCAP 2
Reference: Concept Document, Data Dictionary

Driver Factor Model Factors: MANPOWER POOL CHARACTERISTICS, APTITUDE, PERSONNEL TO BE TRAINED, ENTRY LEVEL CHARACTERISTICS

Factor: ACTUAL CLOSURE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL COORDINATION
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL DEXTERITY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL MOVEMENT JUDGEMENT
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL PERCEPTUAL SPEED/ACCURACY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL REACTION TIME
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL SHORT TERM MEMORY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL STEADINESS/PRECISION
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL VISUALIZATION/SPATIALIZATION SKILLS
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL ACHIEVEMENT
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL ADJUSTMENT
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL AFFILIATION
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL AGREEABLENESS
Model(s): P-CON
Reference: Concept Document
Factor: ACTUAL INTELLECTANCE
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL INTERESTS
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL LOCUS OF CONTROL
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL MASCULINITY
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL POTENCY
Model(s): P-CON
Reference: Concept Document

Factor: DEPENDABILITY
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL VERBAL ABILITY OR INTELLIGENCE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL READING GROUP LEVEL
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL ANTHROPOMETRIC CHARACTERISTICS
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL STRENGTH CATEGORY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL COLOR BLINDNESS
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL DEFECTS IN LOWER EXTREMITIES
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL DEFECTS IN UPPER EXTREMITIES
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL PHYSICAL CAPACITY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document
Factor: ACTUAL VIS. ACUITY CATEGORY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL SEX
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL AFQT GROUP
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL AFQT PERCENTILE SCORE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL GENERAL TECHNICAL APTITUDE SCORE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL HIGHEST CIVILIAN EDUCATION ACHIEVED
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL MAJOR SUBJECT IN COLLEGE
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL SKILLED TECHNICAL STANDARDIZED SCORE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL STATE OF HOME RECORD
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL DATE OF BIRTH
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL ETHNIC GROUP
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL GENERAL MAINT STD SCORE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL MARITAL STATUS
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL RACE
Model(s): P-CON
Reference: Concept Document
Factor: ACTUAL RACIAL/ETHNIC DESCENT
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL OVERALL PHYSICAL CATEGORY
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL MECHANICAL MAINTENANCE STANDARDIZED SCORE
Model(s): P-CON, PERS-EVAL
Reference: Concept Document

Factor: ACTUAL TYPE OF EDUCATIONAL CREDENTIAL
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL SUBSTANCE ABUSE RECORD
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL ARREST RELATED ITEMS
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL FAMILY INCOME
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL FAMILY RELATIONS
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL OVERALL MAP SCORE
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL PARENT'S EDUCATION
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL RELIGIOUS PREFERENCE
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL SCHOOL GRADES
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL WORK HISTORY
Model(s): P-CON
Reference: Concept Document

Factor: ACTUAL KIND OF HIGH SCHOOL ATTENDED
Model(s): P-CON
Reference: Concept Document

Factor: CURRENT PERSONNEL CHARACTERISTICS
Model(s): PERS-EVAL
Reference: Concept Document

Driver Factor Model Factors: MATERIEL & SUPPORT SYSTEM; PROVISIONING; SPARES; POL, AMMO, ETC.

Factor: POL REQUIREMENTS
Model(s): MANCAP 2
Reference: Concept Document

Factor: ROUNDS SPENT
Model(s): MANCAP 2
Reference: Concept Document

Factor: SPARES REQUIREMENTS
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factor: O & O CONCEPT

Factor: SYSTEM DESCRIPTION
Model(s): T-CON
Reference: Concept Document

Factor: BASELINE EQUIPMENT
Model(s): PERS-EVAL
Reference: Concept Document

Factor: FUNCTION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: SYSTEM
Model(s): T-CON, P-CON, MANCAP 2
Reference: Concept Document

Factor: CURRENT SYSTEMS
Model(s): M-CON
Reference: Concept Document

Factor: REPLACEMENT SYSTEMS
Model(s): M-CON
Reference: Concept Document

Factor: SYSTEM CLASS
Model(s): T-CON
Reference: Concept Document

Factor: SYSTEM SUBCLASS
Model(s): T-CON
Reference: Concept Document

Driver Factor Model Factors: O & O CONCEPT, BOIP, ORGANIZATIONAL STRUCTURE

Factor: SYSTEM DENSITY
Model(s): M-CON
Reference: Concept Document

Factor: FORCE STRUCTURE HIERARCHY
Model(s): M-CON
Reference: Concept Document

Factor: UNITS CURRENTLY PERFORMING MISSION
Model(s): M-CON
Reference: Concept Document

Driver Factor Model Factors: O & O CONCEPT, LSA

Factor: COMPONENT CRITICALITY TO MISSION
Model(s): PERS-EVAL
Reference: Concept Document

Factor: CONTACT TEAM - MAXIMUM QUEUE LENGTH
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: O & O CONCEPT, MAINTENANCE CONCEPT

Factor: MAINTENANCE LEVEL
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: O & O CONCEPT, OPTEMPO

Factor: STAND-BY TIME
Model(s): SPARC
Reference: Concept Document

Driver Factor Model Factors: O & O CONCEPT, OPTEMPO, USE RATES, MAINTENANCE BURDEN

Factor: NO. SYSTEMS AVAILABLE
Model(s): MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: O & O CONCEPT, SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS, SYSTEM DESIGN, ROC

Factor: MISSION PERFORM ACCURACY
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: MISSION PROFILE
Model(s): MANCAP 2
Reference: Concept Document, Data Dictionary

Factor: TIME BETWEEN MISSIONS
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK CONDITION SET DESCRIPTION
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK CONDITION SET NUMBER
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK CONDITIONS - FEATURES OF FRIENDLY FIRE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK CONDITIONS - INDUCED STRESSORS
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK CONDITIONS - THREAT CHARACTERISTICS
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK CONDITIONS - ENVIRONMENTAL CONDITIONS
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: TASK IMPACTING CONDITION TYPE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: NEW SYSTEM TASK CONDITIONS
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: PERFORMANCE DEFICIENCIES
Model(s): SPARC
Reference: Concept Document

Factor: ARTIFICIAL LIGHTING
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: ATMOSPHERE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: BIOLOGICAL FACTORS
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: DIRECT GLARE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: DUSK/DAWN
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: FLARES
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: GROUND AND WATER
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: GROUND SLOPE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: GROUND SURFACE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: HUMIDITY
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - ACOUSTICAL NOISE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDIRECT GLARE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - ACCELERATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - BLAST
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - CHEMICAL
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - ECM
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS -ELECTROMAGNETIC RADIATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - EMP
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - MODIFIED ECOLOGY
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - NUCLEAR RADIATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - SHOCK
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - THERMAL ENERGY
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - TRANSITION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - VIBRATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: INDUCED ENVIRONMENTAL CONDITIONS - AIRBORNE CONTAINMENTS
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: MISSION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: OBSTACLES
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: PITCH BLACK
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: PRECIPITATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: TARGET TACTICS
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: CONCEALMENT
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: HARDWARE TYPE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: LOCATION
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: NUMBER
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: SIZE/MOVEMENT
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: SPEED
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: UNIT TYPE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TARGET/THREAT: WEAPONS TYPE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: TEMPERATURE
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: WEATHER: ILLUMINATION; MOONLIGHT
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: WEATHER: ILLUMINATION; STAR LIGHT
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: WEATHER: ILLUMINATION; SUNLIGHT
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: WIND
Model(s): SPARC
Reference: Concept Document, Data Dictionary

Factor: MISSION AREA
Model(s): SPARC, MAN-SEVAL
Reference: Concept Document, Data Dictionary

Driver Factor Model Factors: SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS, OPTEMPO, ROC

Factor: PROBABILITY OF AVAILABILITY
Model(s): SPARC, MANCAP 2
Reference: Concept Document

Factor: EXPECTED SYSTEM AVAILABILITY
Model(s): MAN-SEVAL, MANCAP 2
Reference: Concept Document

Factor: TIME TO PERFORM MISSION
Model(s): PERS-EVAL, MANCAP 2
Reference: Concept Document

Factor: CALCULATED MISSION TIME
Model(s): SPARC, MANCAP 2
Reference: Concept Document

Factor: EXPECTED USAGE RATE OF EQUIPMENT
Model(s): PERS-EVAL, MANCAP 2
Reference: Concept Document

Factor: MAXIMUM MISSION FREQUENCY
Model(s): PERS-EVAL, MANCAP 2
Reference: Concept Document

Factor: MEAN MISSION FREQUENCY
Model(s): MAN-SEVAL, MANCAP 2
Reference: Concept Document

Factor: MEAN MISSION LENGTH
Model(s): MAN-SEVAL, MANCAP 2
Reference: Concept Document

Factor: MISSION LENGTH
Model(s): PERS-EVAL, MANCAP 2
Reference: Concept Document

Factor: MOST LIKELY MISSION FREQUENCY
Model(s): PERS-EVAL, MANCAP 2
Reference: Concept Document

Factor: NUMBER OF MISSIONS PER DAY
Model(s): PERS-EVAL, MAN-SEVAL, MANCAP 2
Reference: Concept Document

Factor: NUMBER OF MISSIONS PER TIME UNIT
Model(s): SPARC, MANCAP 2
Reference: Concept Document

Factor: STANDARD DEVIATION OF MISSION FREQUENCY
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: STANDARD DEVIATION OF MISSION LENGTH
Model(s): MAN-SEVAL
Reference: Concept Document

Factor: MISSION OPERATING TIME
Model(s): SPARC, MANCAP 2
Reference: Concept Document

Factor: MISSION PERFORMANCE TIME
Model(s): SPARC, MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS

Factor: AVERAGE ADMINISTRATIVE & LOG DOWNTIME
Model(s): SPARC
Reference: Concept Document

Factor: AVERAGE MAINTENANCE DOWNTIME
Model(s): SPARC
Reference: Concept Document

Driver Factor Model Factors: SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS, LSA, SYSTEM MAINTENANCE CHARACTERISTICS

Factor: NUMBER OF OPERATIONAL UNITS BEFORE FIRST FAILURE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: PROBABILITY OF MAINTENANCE ACTION GIVEN FAILURE
Model(s): MANCAP 2
Reference: Concept Document

Factor: SOFT/HARDWARE TYPE ASSOCIATED WITH THE NEW SYSTEM TASKS
Model(s): PERS-EVAL
Reference: Concept Document

Factor: MEAN OPERATIONAL UNITS BETWEEN FAILURE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: NUMBER OF OPERATIONAL UNITS BETWEEN SCHEDULED MAINTENANCE
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: NUMBER OF OUTPUT UNITS COMPLETED
Model(s): PERS-EVAL
Reference: Concept Document

Factor: PREVENTIVE MAINTENANCE TASK FREQUENCY
Model(s): PERS-EVAL
Reference: Concept Document

Factor: SYSTEM/COMPONENT DESIGN DESCRIPTION
Model(s): PERS-EVAL
Reference: Concept Document

Factor: SYSTEM COMPONENT DESIGN CLASSIFICATION
Model(s): PERS-EVAL
Reference: Concept Document

Factor: ESTIMATE OF MAINTAINABILITY
Model(s): SPARC
Reference: Concept Document

Factor: EXPECTED FUNCTIONAL SYSTEM RELIABILITY
Model(s): MAN-SEVAL
Reference: Concept Document

Driver Factor Model Factors: SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS, SYSTEM MAINTENANCE CHARACTERISTICS, LSA

Factor: MEAN TIME BETWEEN SUB-SYSTEM FAILURE
Model(s): MANCAP 2
Reference: Concept Document, Data Dictionary

Factor: SIMULATED RELIABILITY
Model(s): PERS-EVAL
Reference: Concept Document

Factor: SYSTEM FAILURE RATE
Model(s). MANCAP 2
Reference: Concept Document

Factor: ESTIMATED SYSTEM RELIABILITY
Model(s): SPARC
Reference: Concept Document

Factor: CALCULATED SYSTEM RELIABILITY
Model(s): SPARC
Reference: Concept Document

Factor: FAILURE RATE FOR EQUIPMENT
Model(s): PERS-EVAL
Reference: Concept Document

Factor: MAINTENANCE REQUIREMENT
Model(s): MANCAP 2
Reference: Concept Document

Factor: SYSTEM RELIABILITY
Model(s): SPARC, MANS-EVAL, MANCAP 2
Reference: Concept Document

Driver Factor Model Factors: QQPRI, KSAs, PERSONNEL REQUIREMENTS

Factor: PREDICTED AFQT PERCENTILE SCORE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED ANTHROPOMETRIC CHARACTERISTICS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED ARREST RELATED ITEMS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED CLOSURE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED COLOR BLINDNESS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED COORDINATION
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED DEFECTS IN LOWER EXTREMITIES
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED DEFECTS IN UPPER EXTREMITIES
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED DEXTERITY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED FAMILY INCOME
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED FAMILY RELATIONS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED GENERAL TECHNICAL APTITUDE SCORE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED HIGHEST CIVILIAN EDUCATION ACHIEVED
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED KIND OF HIGH SCHOOL ATTENDED
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED MAJOR SUBJECT IN COLLEGE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED MECHANICAL MAINTENANCE STANDARDIZED SCORE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED MOVEMENT JUDGEMENT
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED OVERALL MAP SCORE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED PARENT'S EDUCATION
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED PERCEPTUAL SPEED/ACCURACY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED PHYSICAL CAPACITY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED REACTION TIME
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED RELIGIOUS PREFERENCE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED SCHOOL GRADES
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED SEX
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED SHORT TERM MEMORY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED SKILLED TECHNICAL STANDARDIZED SCORE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED STATE OF HOME RECORD
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED STEADINESS/PRECISION
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED STRENGTH CATEGORY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED SUBSTANCE ABUSE RECORD
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED TYPE OF EDUCATIONAL CREDENTIAL
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED VISUAL ACUITY CATEGORY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED VISUALIZATION AND SPATIALIZATION SKILLS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED WORK HISTORY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED RACIAL/ETHNIC DESCENT
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED ACHIEVEMENT
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED ADJUSTMENT
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED AFFILIATION
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED AFQT GROUP
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED AGREEABLENESS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED DATE OF BIRTH
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED DEPENDABILITY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED ETHNIC GROUP
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED INTELLECTANCE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED INTERESTS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED LOCUS OF CONTROL
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED MARITAL STATUS
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED MASCULINITY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED POTENCY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED RACE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED VERBAL ABILITY OR GENERAL INTELLIGENCE
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED OVERALL PHYSICAL CATEGORY
Model(s): P-CON
Reference: Concept Document

Factor: PREDICTED READING GROUP LEVEL
Model(s): P-CON
Reference: Concept Document

Factor: NEW SYSTEM TASK PERSONNEL CHARACTERISTICS
Model(s): PERS-EVAL
Reference: Concept Document

Factor: AUDITORY CHANNEL WORKLOAD FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: COGNITIVE PROCESSES CHANNEL WORKLOAD FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: PSYCHOMOTOR CHANNEL WORKLOAD FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: VISUAL CHANNEL WORKLOAD FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document, Data Dictionary

Factor: OVERALL PHYSICAL EFFORT FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document

Factor: PHYSICAL STRENGTH DEMANDS FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document

Driver Factor Model Factors: QQPRI, SYSTEM PERFORMANCE REQUIREMENTS & CONSTRAINTS

Factor: FEEDBACK FOR COMPONENT
Model(s): PERS-EVAL
Reference: Concept Document

Driver Factor Model Factors: QQPRI, PERSONNEL REQUIREMENTS

Factor: PERSONNEL CHARACTERISTIC
Model(s): PERS-EVAL
Reference: Concept Document

Driver Factor Model Factors: QQPRI, TASK PERFORMANCE REQUIREMENTS (TPR)

Factor: PROCEDURAL COMPLEXITY FOR COMPONENT AND TASK
Model(s): PERS-EVAL
Reference: Concept Document

Driver Factor Model Factors: QQPRI, TRAINING DEVICES

Factor: SYSTEM TRAINING DEVICES
Model(s): T-CON
Reference: Concept Document

Driver Factor Model Factors: QQPRI, TRAINING REQUIREMENTS

Factor: SYSTEM TRAINING FOR REPAIR/SERVICE TIME
Model(s): T-CON
Reference: Concept Document

Factor: SYSTEM TRAINING FOR TROUBLESHOOTING TIME
Model(s): T-CON
Reference: Concept Document

Driver Factor Model Factors: SUMMATIVE MANPOWER, BOIP, LEVEL OF MAINTENANCE

Factor: MANPOWER REQUIREMENTS - ID
Model(s): M-CON, MANCAP 2
Reference: Concept Document

Factor: MANPOWER REQUIREMENTS - IG
Model(s): M-CON, MANCAP 2
Reference: Concept Document

Factor: MANPOWER REQUIREMENTS - O
Model(s): M-CON, MANCAP 2
Reference: Concept Document

Driver Factor Model Factor: TASK

Factor: TASK
Model(s): SPARC, PERS-EVAL, MANCAP 2
Reference: Concept Document, Data Dictionary

Driver Factor Model Factors: TRAINING DEVICE, TRAINING SUBSYSTEM

Factor: PERCENT TIME FOR EACH TRAINING MEDIA FOR TASK
Model(s): PERS-EVAL, T-CON
Reference: Concept Document

Factor: EXPECTED TRAINING MEDIA FOR TASK
Model(s): PERS-EVAL, T-CON
Reference: Concept Document

Driver Factor Model Factors: TRAINING REQUIREMENTS, TRAINING SUBSYSTEM

Factor: PREDICTED LENGTH OF TASK TRAINING
Model(s): PERS-EVAL, T-CON
Reference: Concept Document

Factor: TRANSFER OF TRAINING RATIO FOR MEDIA
Model(s): PERS-EVAL, T-CON
Reference: Concept Document

Factor: ESTIMATED TIME TO TRAIN NEW SYSTEM TASK
Model(s): PERS-EVAL, T-CON
Reference: Concept Document

Factor: TASK TRAINING TIME ESTIMATE
Model(s): PERS-EVAL, T-CON
Reference: Concept Document

Factor: SUSTAINMENT TRAINING FREQUENCY
Model(s): T-CON
Reference: Concept Document, Data Dictionary

APPENDIX D

DRIVER FACTOR MODEL FACTORS

This appendix lists the factors found in the Evans and Roth Driver Factor Model displayed in Figure 1 by the factor source(s) or driver factor(s) within the model. This listing, although lacking in the visual structure apparent in Figure 1, allows one to more easily identify all sources that have an input into any one factor.

DRIVER FACTOR MODEL FACTORS

Factor Name: SYSTEM MAINTENANCE CHARACTERISTICS
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (ROC)

Factor Name: BOIP
Factor Source(s): OPTEMPO, TMDE, SPARES, POL ETC., TPR, QQPRI
Factor Type: DOCUMENT

Factor Name: NO. PEOPLE IN MANPOWER POOL
Factor Source(s): DRIVER
Factor Type: NOT IN DOCUMENT SPECIFICALLY

Factor Name: TASK ALLOCATION STRATEGY
Factor Source(s): MAINTENANCE CONCEPT
Factor Type: IN DOCUMENT (O & O PLAN)

Factor Name: TESTABILITY INITIATIVES
Factor Source(s): DRIVER
Factor Type: NOT IN DOCUMENT

Factor Name: SYSTEM MAINTENANCE PROFILE (TASKS BY LEVEL)
Factor Source(s): MAINTENANCE CONCEPT
Factor Type: IN DOCUMENT (MAC)

Factor Name: FAILURE MODES ANALYSIS
Factor Source(s): SYSTEM DESIGN
Factor Type: NOT IN DOCUMENT

Factor Name: SUMMATIVE MANPOWER REQUIREMENTS
Factor Source(s): MAINTENANCE CONCEPT, QQPRI, KSAs, MAINTENANCE BURDEN
Factor Type: IN DOCUMENT (SMMP, BOIP)

Factor Name: ACCESSIBILITY DESIGN INITIATIVES
Factor Source(s): DRIVER
Factor Type: NOT IN DOCUMENT

Factor Name: MOSs
Factor Source(s): SKILL NEEDS, KSAs, APT, MOS DATA, LEVEL OF MAINTENANCE, GOALS & CONSTRAINTS
Factor Type: IN DOCUMENT (SMMP, BOIP)

Factor Name: APTITUDE (MANPOWER POOL CHARACTERISTIC)
Factor Source(s): DRIVER
Factor Type: IN DOCUMENT (SMMP)

Factor Name: SERVICE AND REPAIR TASKS
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (MAC)

Factor Name: TASKS
Factor Source(s): MAINTENANCE TASKS
Factor Type: IN DOCUMENT (MAC)

Factor Name: MANPOWER POOL CHARACTERISTICS
Factor Source(s): DRIVER
Factor Type: IN DOCUMENT (SMMP)

Factor Name: FAILURE MODES, COMPONENTS
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (ROC)

Factor Name: SYSTEM PERFORMANCE CONSTRAINTS
Factor Source(s): ROC
Factor Type: IN DOCUMENT (ROC)

Factor Name: SYSTEM DESIGN
Factor Source(s): ROC
Factor Type: IN DOCUMENT (ROC)

Factor Name: TRAINING REQUIREMENTS
Factor Source(s): APTITUDES, KSAs, QQPRI
Factor Type: IN DOCUMENT (SMMP, STRAP)

Factor Name: QQPRI
Factor Source(s): KSAs, BOIP, EXISTING MOS DATA
Factor Type: DOCUMENT

Factor Name: PERSONNEL REQUIREMENTS
Factor Source(s): TTHS DATA, MOSs, MANPOWER, QQPRI, TRAINING REQUIREMENTS, ORGANIZATIONAL STRUCTURES
Factor Type: IN DOCUMENT (QQPRI)

Factor Name: LOGISTICAL SUPPORT ANALYSIS (LSA)

Factor Source(s): SYSTEM DESIGN, MAINTENANCE TASKS
Factor Type: IN DOCUMENT (LSAR REPORTS)

Factor Name: MATERIEL AND SUPPORT SYSTEMS
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (ROC)

Factor Name: TASK PERFORMANCE REQUIREMENTS (TPR)
Factor Source(s): MAINTENANCE BURDEN
Factor Type: IN DOCUMENT (SMMP, MAC, STRAP)

Factor Name: TASKS AND LEVELS
Factor Source(s): SYSTEM MAINTENANCE PROFILE
Factor Type: IN DOCUMENT (MAC)

Factor Name: BIT/BITE USE
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (ROC)

Factor Name: EXISTING MOS DATA
Factor Source(s): NONE
Factor Type: IN DOCUMENT (SMMP)

Factor Name: TOE
Factor Source(s): LEVEL OF MAINTENANCE, MOSs, BOIP, TMDE, SPARES AND POL, QQPRI, ORGANIZATIONAL CONCEPTS
Factor Type: DOCUMENT

Factor Name: TRAINING SUBSYSTEM
Factor Source(s): ENTRY LEVEL CHARACTERISTICS, TRAINING REQUIREMENTS, PERSONNEL TO BE TRAINED, ORGANIZATIONAL CONCEPTS
Factor Type: IN DOCUMENT (STRAP)

Factor Name: FAULT ISOLATION TASKS
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (MAC)

Factor Name: MAINTENANCE CONCEPT
Factor Source(s): O & O CONCEPT
Factor Type: IN DOCUMENT (O & O PLAN)

Factor Name: NUMBER OF SYSTEMS PER UNIT

Factor Source(s): O & O CONCEPT
Factor Type: IN DOCUMENT (BOIP)

Factor Name: DOCUMENTATION
Factor Source(s): LOGISTICAL SUPPORT ANALYSIS
Factor Type: NOT IN DOCUMENT

Factor Name: MAINTENANCE TASKS
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (MAC)

Factor Name: TMDE
Factor Source(s): LOGISTICAL SUPPORT ANALYSIS
Factor Type: IN DOCUMENT (BOIP)

Factor Name: SYSTEM PERFORMANCE REQUIREMENTS
Factor Source(s): ROC
Factor Type: IN DOCUMENT (ROC)

Factor Name: POL, AMMO, ETC
Factor Source(s): LOGISTICAL SUPPORT ANALYSIS
Factor Type: IN DOCUMENT (LSAR REPORT)

Factor Name: TECHNOLOGICAL OPPORTUNITIES
Factor Source(s): ROC
Factor Type: NOT IN DOCUMENT

Factor Name: LEVELS OF MAINTENANCE
Factor Source(s): MAINTENANCE CONCEPT
Factor Type: IN DOCUMENT (O & O PLAN)

Factor Name: OPTEMPO (FREQUENCY OF USE)
Factor Source(s): O & O CONCEPT
Factor Type: IN DOCUMENT (O & O PLAN)

Factor Name: SPARES
Factor Source(s): LOGISTICAL SUPPORT ANALYSIS
Factor Type: IN DOCUMENT (LSAR REPORT)

Factor Name: MAINTENANCE BURDEN (TASKS, LEVELS, USE, NUMBER OF SYSTEMS)
Factor Source(s): SYSTEM MAINTENANCE PROFILE, OPTEMPO, SYSTEM DESIGN, TMDE, SPARES
Factor Type: NOT IN DOCUMENT

Factor Name: O & O CONCEPT
Factor Source(s): DRIVER
Factor Type: IN DOCUMENT (O & O PLAN)

Factor Name: KNOWLEDGE, SKILLS, ABILITY REQUIREMENTS (KSAs)
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (SMMP, STRAP)

Factor Name: BIT/BITE CAPABILITY
Factor Source(s): SYSTEM DESIGN
Factor Type: IN DOCUMENT (ROC)

Factor Name: PROVISIONING
Factor Source(s): SPARES
Factor Type: IN DOCUMENT (LSAR REPORT)

Factor Name: NUMBERS OF SYSTEMS (EACHES)
Factor Source(s): OPTEMPO
Factor Type: IN DOCUMENT (BOIP)

Factor Name: TMDE CAPABILITIES
Factor Source(s): TMDE
Factor Type: IN DOCUMENT (ROC)

Factor Name: MAINTENANCE STRATEGY
Factor Source(s): O & O CONCEPT
Factor Type: IN DOCUMENT (O & O PLAN), SOMETIMES; ELSE SETB Y POLICY

Factor Name: USE RATES
Factor Source(s): OPTEMPO
Factor Type: IN DOCUMENT (ROC; O & O PLAN)

Factor Name: MANPOWER
Factor Source(s): SUMMATIVE MANPOWER REQUIREMENTS
Factor Type: IN DOCUMENT (SMMP, BOIP)

Factor Name: HFE DESIGN INITIATIVES
Factor Source(s): DRIVER
Factor Type: NOT IN DOCUMENT

Factor Name: MAINTAINABILITY DESIGN INITIATIVES
Factor Source(s): DRIVER
Factor Type: NOT IN DOCUMENT

Factor Name: TTHS FACTORS DATA
Factor Source(s): OUTSIDE FACTOR
Factor Type: IN DOCUMENT (SMMP), SOMETIMES

Factor Name: REQUIRED OPERATIONAL CAPABILITY (ROC)
Factor Source(s): DRIVER
Factor Type: DOCUMENT

Factor Name: ENTRY LEVEL CHARACTERISTICS
Factor Source(s): MANPOWER POOL CHARACTERISTICS
Factor Type: IN DOCUMENT (SMMP)

Factor Name: PERSONNEL TO BE TRAINED
Factor Source(s): TOE
Factor Type: IN DOCUMENT (SMMP; STRAP; TOE)

Factor Name: ORGANIZATIONAL CONCEPTS
Factor Source(s): O & O CONCEPT
Factor Type: IN DOCUMENT (O & O PLAN)

Factor Name: ORGANIZATIONAL STRUCTURES
Factor Source(s): TOE
Factor Type: IN DOCUMENT (TOE)

Factor Name: TMDE
Factor Source(s): LSA
Factor Type: DOCUMENT (MAC)

APPENDIX E

Tables For PHASE 2

Table 1

Independent Factors

Factor	Nomenclature	Definition	Metafactor Represented
SYS_TYPE	System Type	Category of System	O & O Plan, System
USE	System Use	Environmental Conditions under which the System is Used	O & O Plan, System
MOS_TYPE	MOS Type	Category of maintenance person	MOS, BOIP
LOM	Level of Maintenance	Numbers of Levels of Maintenance associated with System	Maintenance Concept
MAINTLVL	Maintenance Level	Maintenance Level at which Tasks are Performed by MOS Type	Maintenance Concept, Maintenance Profile
PRED_TST	Predicted Mean Time to Perform Test Tasks	Predicted Mean Time for Testing Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile
PRED_INS	Predicted Mean Time to Perform Inspection Tasks	Predicted Mean Time for Inspection Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile

Factor	Nomenclature	Definition	Metafactor Represented
PRED_ADJ	Predicted Mean Time to Perform Adjustment Tasks	Predicted Mean Time for Adjustment Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile
PRED_RPL	Predicted Mean Time to Perform Replacement Tasks	Predicted Mean Time for Replacement Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile
PRED_R_I	Predicted Mean Time to Perform Remove or Install Tasks	Predicted Mean Time for Remove or Install Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile
PRED_RPR	Predicted Mean Time to Perform Repair Tasks	Predicted Mean Time for Repair Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile

Factor	Nomenclature	Definition	Metafactor Represented
PRED_SER	Predicted Mean Time to Perform Service Tasks	Predicted Mean Time for Service Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile
PRED_OTH	Predicted Mean Time to Perform Other Tasks	Predicted Mean Time for Other Tasks as Performed on System at Maintenance Level and by MOS Type	Tasks, Maintenance Profile
USE_RATE	Frequency of Use	The number of hours the system is used in a year	OPTEMPO
MN_AFQT	Mean Armed Forces Qualification Test (AFQT) Score	Mean AFQT for MOS Type	Manpower Pool Characteristics Personnel to be trained
RET_RTE	Retention Rate	Percent of First Termers of MOS Type Retained	Availability
PRED_ASS	Predicted Assignment	Numbers of Personnel of MOS Type Predicted to be Available for Assignment	Availability
PER_HS	Percent Completed High School	Percent of Personnel in MOS Type who have completed High School	Manpower Pool Characteristics Personnel to be Trained

Factor	Nomenclature	Definition	Metafactor Represented
AUTHOR	Number of Positions Authorized	Number of Personnel of MOS Type Authorized for Distribution among Units	Availability
OPER	Number of Positions Operational	Number of Personnel of MOS Type Actually Distributed among Units	Availability
TRAIN_LE	Length of Training	Number of Days of Training Received in Basic Course for MOS Type	Training System
PRED_DPA	Predicted Direct Productive Annual Maintenance Manhours	Predicted Productive Annual Maintenance Manhours for the MOS Type and Maintenance Level for System	System Maintenance Characteristics
PRED_MTB	Predicted Mean Time Between Failures	Predicted Mean Time Between Failures for System	System Maintenance Characteristics
SYS1	Transport Helicopter	Subcategory of SYS_TYPE	O & O Plan, System
SYS2	Scout Helicopter	Subcategory of SYS_TYPE	O & O Plan, System
SYS3	Tank	Subcategory of SYS_TYPE	O & O Plan, System

Factor	Nomenclature	Definition	Metafactor Represented
SYS4	Armored Personnel Carrier	Subcategory of SYS_TYPE	O & O Plan, System
SYS5	Fighting Vehicle-Tracked	Subcategory of SYS_TYPE	O & O Plan, System
SYS6	Light Truck	Subcategory of SYS_TYPE	O & O Plan, System
SYS7	Heavy Truck	Subcategory of SYS_TYPE	O & O Plan, System
SYS8	Big Gun	Subcategory of SYS_TYPE (Subcategory of SYS_TYPE resulting from zeros in all other SYS_TYPE subcategories is missile launcher)	O & O Plan, System
USE1	Air	Subcategory of USE	O & O Plan, System
USE2	Water	Subcategory of USE	O & O Plan, System
USE3	Rough Terrain Especially	Subcategory of USE	O & O Plan, System
USE4	Dragged/ Stationary	Subcategory of USE	O & O Plan, System
USE5	Roads	Subcategory of USE	O & O Plan, System

Factor	Nomenclature	Definition	Metafactor Represented
USE6	All Terrain	Subcategory of USE (USE subcategory resulting from zeros in USE* categories is air and dragged combined, for missile launcher system type)	O & O Plan, System
MOS1	Hydraulic/ Pnuedraulics	Subcategory of MOS_TYPE	BOIP, MOS
MOS2	Electrical	Subcategory of MOS_TYPE	BOIP, MOS
MOS3	Avionics and Radio	Subcategory of MOS_TYPE	BOIP, MOS
MOS4	Turret	Subcategory of MOS_TYPE	BOIP, MOS
MOS5	Armament	Subcategory of MOS_TYPE	BOIP, MOS
MOS6	Sighting/ Fire Control	Subcategory of MOS_TYPE	BOIP, MOS
MOS7	Power Train/ Power Plant	Subcategory of MOS_TYPE	BOIP, MOS
MOS8	General Repair	Subcategory of MOS_TYPE	BOIP, MOS
MOS9	Structure	Subcategory of MOS_TYPE (Artillery Repairer, MOS code 10, represented by zero on all MOS* factors)	BOIP, MOS

Factor	Nomenclature	Definition	Metafactor Represented
LOM1	Three Levels of Maintenance	Subcategory of LOM (Zero coding indicates four levels of maintenance)	Maintenance Concept
MTL1	Unit Level Maintenance	Subcategory of MAINTLVL	Maintenance Concept, Maintenance Profile
MTL2	Direct Support Level Maintenance	Subcategory of MAINTLVL (General Support Level represented by zero coding of both MTL1 and MTL2)	Maintenance Concept, Maintenance Profile

Table 2

Dependent Variables

Variable	Definition
ACT_TST	Actual Mean Time to Perform Test Tasks
ACT_INS	Actual Mean Time to Perform Inspection Tasks
ACT_ADJ	Actual Mean Time to Perform Adjustment Tasks
ACT_RPL	Actual Mean Time to Perform Replacement Tasks
ACT_R_I	Actual Mean Time to Perform Remove or Install Tasks
ACT_RPR	Actual Mean Time to Perform Repair Tasks
ACT_OVRH	Actual Mean Time to Perform Overhaul Tasks
ACT_SERV	Actual Mean Time to Perform Service Tasks
ACT_OTH	Actual Mean Time to Perform Other Tasks

Table 3

Target Systems and System Designator for Factor SYS_TYPE

System	System Designator	System Designator Definition
UH-60A	1	Transport Helicopter
CH-47D	2	Scout Helicopter
M1A1	3	Tank
(No system)	4	Armored Personnel Carrier
M2A1	5	Fighting Vehicle - Tracked
M1038	6	Light Truck
M9777	7	Heavy Truck
M198	8	Big Gun
IHAWK	9	Missile Launcher
VULCAN	8	Air Defense Gun

Table 4

Data Sources for Target Systems

	M977	UH-60	M198	M1A1	M2	IHAWK	CH-47D	HMMWV	VULCAN
O&O		06/06/86							
ROC						11/16/88	12/02/74		
BOIP	06/21/82 10/16/80	10/10/85		06/24/87	10/23/89	10/10/89	11/13/89		
QQPRI	06/21/82	10/10/85		06/24/87	X		02/21/86		
SMMP		10/00/89			02/06/87				
MAC	X	X	X	X	X	X	X	X	X
JSOR	05/12/80 06/20/80								
MN		08/00/79	04/05/77	06/30/80	03/02/78				
LOA	12/15/78								
LSAR		X		X	X				
JEMNS								09/14/80T	

Table 5

MOS Classifications

MOS Numerical Assignment	MOS Task Focus
1	Hydraulic/Pneudraulic
2	Electrical
3	Avionics and Radio
4	Turret
5	Armament
6	Sighting/Fire Control
7	Power Train/Power Plant
8	General Repair
9	Structure
10	Weapons

Table 6

MOS and Assigned Classification Numbers

Mos Name	MOS Title	Classification
21G	PERSHING Electronics Material Specialist	8
24C	Hawk Firing Section Mechanic	8
24E	Hawk Fire Control Mechanic	8
24G	Hawk Information Coordination Central Mechanic	8
24H	Hawk Fire Control Repairer	5
24J	Hawk Pulse Radar Repairer	3
24K	Hawk Continuous Wave Radar Repairer	3
24L	Hawk Launcher and Mechanical Systems Repairer	8
24M	VULCAN System Mechanic	8
24R	Hawk Master Mechanic	8
24T	PATRIOT Operator and System Mechanic	8
25L	AN/TSQ 73 Air Defense Artillery Command and Control Operator/Repairer	3
26E	Aerial Radar Sensor Repairer	3
26K	Aerial Electronic Warning/Defense Equipment Repairer	3

Mos Name	MOS Title	Classification
27E	Tow/Dragon Repairer	8
27F	VULCAN Repairer	8
27H	Hawk Firing Section Repairer	5
27J	Hawk Field Maintenance Equipment/Pulse Acquisition Radar Repairer	3
27M	MLRS Repairer	8
29E	Radio Repairer	3
31E	Field Radio Repairer	3
31K	Combat Signaler	9
31M	Multichannel Communications System Operator	3
31V	Unit Level Communications Maintainer	8
35B	Electronic Instrument Repairer	2
35E	Special Electronics Devices Repairer	2
35H	Test, Measurement, and Diagnostic Equipment Maintenance Support Specialist	8
35K	Avionic Mechanic	3
35M	Avionic Navigation and Flight Control Equipment Repairer	3
35P	Avionic Equipment Maintenance Supervisor	3

Mos Name	MOS Title	Classification
35R	Avionic Special Equipment Repairer	3
41C	Fire Control Instrument Repairer	6
43M	Fabric Repair Specialist	8
44B	Metal Repairer	8
44E	Machinist	8
45B	Small Arms Repairer	10
45D	Self-Propelled Field Artillery Turret Mechanic	4
45E	M1 ABRAMS Tank Turret Mechanic	4
45G	Fire Control Systems Repairer	6
45K	Tank Turret Repairer	4
45L	Artillery Repairer	10
45N	M60A1/A3 Tank Turret Mechanic	4
45T	BRADLEY Fighting Vehicle System Turret Mechanic	4
45Z	Armament/Fire Control Maintenance Supervisor	5
52C	Utilities Equipment Repairer	8
52D	Power-Generation Equipment Repairer	8
52G	Transmission and Distribution Specialist	8

Mos Name	MOS Title	Classification
54B	Chemical Operations Specialist	8
54E	Nuclear, Biological, and Chemical Specialist	8
55D	Explosive Ordnance Disposal	10
62B	Construction Equipment Repairer	8
63B	Light-Wheel Vehicle Mechanic	7
63D	Self-Propelled Field Artillery System Mechanic	10
63E	M1 ABRAMS Tank System Mechanic	8
63G	Fuel and Electrical Systems Repairer	2
63H	Track Vehicle Repairer	8
63J	Quartermaster and Chemical Equipment Repairer	8
63N	M60A1/A3 Tank System Mechanic	8
63S	Heavy-Wheel Vehicle Mechanic	8
63T	BRADLEY Fighting Vehicle System Mechanic	8
63W	Wheel Vehicle Repairer	8
65E	Airbrake Repairer	8
66T	Tactical Transport Helicopter Technical Inspector	8

Mos Name	MOS Title	Classification
67T	UH-60 Helicopter Repairer	8
67H	Observation Airplane Repairer	8
67U	CH-47 Helicopter Repairer	8
68B	Aircraft Powerplant Repairer	7
68D	Aircraft Powertrain Repairer	7
68F	Aircraft Electrician	2
68G	Aircraft Structural Repairer	9
68H	Aircraft Pneudraulics Repairer	1
68J	Aircraft Armament/Missile Systems Repairer	5
68M	Aircraft Weapons System Repairer	10
68N	Avionic Mechanic	3
68Q	Avionic Flight Systems Repairer	3
68R	Avionic Radar Repairer	3
92C	Petroleum Laboratory Specialist	8

Table 7

System Use Designators

System Use	Designation for System
Air	1
Water	2
Rough Terrain especially	3
Dragged/Stationary	4
Roads	5
All Terrain	6
Air and Dragged/Stationary	7

Table 8

Uses Assigned to Target Systems

System	System Use Designation
M198	7
M1A1	3
HMMWV	6
IHAWK	7
M2A1	3
UH-60A	1
CH-47D	1
HEMTT	6
VULCAN	7

Table 9

Dependent Variable
Actual Mean Time to Repair (ACT_RPR)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
LOM1	3.78273	.38385	.20	.4641 (159) P=.000	3
PRED_OVR	5.76397	.38325	.10	.4332 (93) P=.000	2
MN_AFQT	-.09035	-.21299	.04	-.1126 (112) P=.237	3
Constant	5.59682				

Multiple R	.60674
R-Squared	.36813
Adjusted R-Squared	.34026
Standard Error	3.91186

F = 13.206 Significance of F < .001

Table 10

Dependent Variable
Actual Mean Time to Remove or Replace (ACT_R_I)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_SER	1.50118	.40829	.11	.3869 (26) P=.051	1
PRED_OVR	1.54893	.33045	.08	.3041 (26) P=.131	1
Constant	-.03069				

Multiple R	.50840
R-Squared	.25847
Adjusted R-Squared	.19399
Standard Error	1.34757

F = 4.008 Significance of F < .032

Table 11

Dependent Variable
Actual Mean Time to Service (ACT_SERV)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_OVR	5.05578	.61535	.18	.4326 (78) P=.000	2
MTL1	1.70519	.31010	.06	.2000 (145) P=.016	3
PRED_TST	.77562	.37702	.06	.1536 (80) P=.174	2
TRAIN_LE	-.01768	-.42497	.03	-.1633 (107) P=.093	3
MOS1	-3.40489	-.20268	.07	.0560 (145) P=.504	3
USE3	1.72741	.27769	.03	.1521 (145) P=.068	3
Constant	2.06919				

Multiple R	.69747
R-Squared	.48646
Adjusted R-Squared	.43906
Standard Error	1.97053

F = 10.262 Significance of F < .001

Table 12

Dependent Variable
Actual Mean Time to Replace (ACT_RPL)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
RET_RTE	-23009.68	-417.8538	.36	-.6122 (64) P=.000	2
PRED_R_I	703.07519	140.94357	.33	.5615 (43) P=.000	1
PRED_RPL	1233.8756	-249.7842	.12	-.2113 (43) P=.174	1
MOS4	-6459.759	-261.8896	.07	-.0743 (107) P=.447	3
PRED_OTH	848.85263	72.69970	.11	.3275 (43) P=.032	1
PRED_SER	-1536.594	-110.0355	.003(0)	-.2699 (42) P=.084	1
SYS1	-3806.335	-267.9040	0	.2181 (107) P=.024	3
MN_AFQT	-57.79932	-115.0990	0	-.2453 (62) P=.055	2
PRED_INS	6294.0122	386.64914	0	.2167 (43) P=.163	1
MOS9	-12449.18	-448.0511	0	.0661 (107) P=.333	3

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_OVR	7261.9875	407.91026	0	.1132 (42) P=.475	1
PRED_TST	1037.1711	232.66849	0	-.1295 (43) P=.408	1
LOM1	-7876.016	-675.1615	0	-.4194 (107) P=.000	3
PRED_MTB	-3.73834	-136.4592	0	-.3331 (100) P=.001	3
SYS8	-4246.530	-295.3263	0	-.3151 (100) P=.001	3
MOS6	-3983.469	-177.3549	0	-.1320 (107) P=.175	3
AUTHOR	-2.43833	-947.0901	0	-.0923 (89) P=.390	2
USE_RATE	-.35024	-156.3967	0	-.2074 (99) P=.039	2
PRED_ASS	2.32950	997.76954	0	-.0995 (90) P=.351	2
MOS7	-7484.057	-303.4164	0	.5512 (107) P=.000	3
MOS2	-3456.232	-147.2111	0	.0769 (107) P=.431	3
MOS8	-2730.253	-233.3338	0	-.0945 (107) P.333	3

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
TRAIN_LE	-22.16388	-245.9018	0	-.0850 (66) P=.498	2
MOS1	-6024.824	-165.5118	0	.1385 (107) P=.155	3
PRED_ADJ	-2528.036	-199.2465	0	-.2119 (43) P=.163	2
PRED_RPR	-34.410	-48.56110	0	-.1045 (43) P=.505	2
PER_HS	-6361.508	-45.84460	0	-.3560 (68) P=.003	2
MTL1	322.78062	27.09008	0	.0910 (107) P=.351	3
MOS3	-403.2671	-27.69558	0	-.1172 (107) P=.229	3
MOS5	-290.7418	-11.78716	0	-.1089 (107) P=.264	3
MTL2	-12.06743	-1.05870	0	.0501 (107) P=.609	3
Constant	37415.360				

Multiple R	.99872	(results after step 5)
R-Squared	.99744	
Adjusted R-Squared	.99708	
Standard Error	.30785	

F = 2805.000 Significance of F < .001

Table 13

Dependent Variable
Actual Time to Test (ACT_TST)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_RPR	41.58383	76.50056	.63	.7983 (78) P=.000	2
RET_RTE	-8663.782	-205.0936	.21	-.3900 (85) P=.000	2
MOS3	-375.7269	-33.63780	.10	.0217 (121) P=.813	3
MOS7	-2388.980	-126.2540	.06	.1392 (121) P=.128	3
MN_AFQT	25.66823	66.63085	0	.0532 (85) P=.629	2
PRED_MTB	-17.22326	-819.5406	0	-.1490 (114) P=.114	3
TRAIN_LE	4.38838	63.46743	0	.1394 (86) P=.201	2
SYS6	9658.0401	536.23794	0	-.0950 (121) P=.300	3
USE1	-5117.476	-571.8572	0	.2298 (121) P=.011	3
SYS3	-4153.623	-308.2026	0	-.0654 (121) P=.476	3

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
SYS8	-2104.306	-190.7688	0	-.0586 (121) P=.523	3
MOS2	-1347.448	-74.81361	0	.3505 (121) P=.000	3
PRED_RPL	-102.7575	-27.11677	0	-.0841 (78) P=.464	2
SYS2	-266.7221	-23.87889	0	.1194 (121) P=.192	3
OPER	-9.41E-03	-4.99753	0	-.0881 (105) P=.371	3
MTL2	-12.71911	-1.45460	0	.1331 (121) P=.146	3
Constant	9534.0204				

Multiple R	.97209	(after step 3)
R-Squared	.94496	
Adjusted R-Squared	.94254	
Standard Error	1.04837	

F = 389.189 Significance of F < .001

Table 14

Dependent Variable
Actual Mean Time for Other Tasks (ACT_OTH)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_OVR	287.05277	20.39984	.17	.4412 (42) P=.003	1
PRED_R_I	34.42993	8.73244	.16	.4101 (43) P=.006	1
RET_RTE	-885.2262	-20.33874	.07	-.2926 (64) P=.019	2
SYS1	-142.9344	-12.72814	.09	-.0225 (108) P=.817	3
PRED_RPL	-54.41585	-13.93719	.12	-.1997 (43) P=.199	1
MOS7	-304.7498	-15.63153	.12	.0609 (108) P=.531	3
MOS9	-477.6906	-21.75152	.12	.0604 (108) P=.534	3
PRED_INS	214.64629	16.68280	.09	-.0241 (43) P=.878	1
USE1	-302.6765	-32.82734	0	.1452 (108) P=.134	3
MOS4	-269.6839	-13.83289	0	.0116 (108) P=.905	3

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
MOS2	-134.0826	-7.22547	0	.0250 (108) P=.797	3
PRED_SER	-59.99895	-5.43592	0	-.1356 (42) P=.392	1
PRED_MTB	-.14336	-6.62083	0	-.1318 (101) P=.189	3
MOS6	-155.9460	-8.78440	0	-.0603 (108) P=.535	3
MOS1	-221.2891	-7.69131	0	.0152 (108) P=.876	3
MN_AFQT	-3.20902	-8.08494	0	-.0005 (62) P=.997	2
SYS8	-159.4864	-14.03291	0	-.0884 (108) P=.363	3
MOS8	-121.0789	-13.09179	0	-.0805 (108) P=.408	3
TRAIN_LE	-.80308	-11.27271	0	-.0062 (66) P=.961	2
PRED_TST	52.64998	14.94312	0	-.1391 (43) P=.374	1
PRED_ADJ	-132.8427	-13.24649	0	-.2369 (43) P=.126	1
PRED_DPA	.09225	6.05468	0	-.0644 (108) P=.508	3

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
USE_RATE	-.01215	-6.86357	0	-.0921 (100) P=.362	3
PRED_OTH	52.89740	5.73179	0	.1825 (43) P=.242	1
PRED_ASS	.04627	25.07266	0	.0252 (91) P=.813	2
OPER	-.04150	-21.39744	0	.0273 (91) P=.797	2
PRED_RPR	-2.02985	-3.62435	0	-.0482 (43) P=.759	1
PER_HS	-439.1370	-4.00391	0	-.0650 (68) P=.599	2
MTL2	-20.63356	-2.29027	0	-.0823 (108) P=.397	3
MTL1	-19.86670	-2.10952	0	.1472 (108) P=.128	3
MOS5	-11.08917	.56880	0	-.0691 (108) P=.477	3
MOS3	1.82328	.15843	0	.0894 (108) P=.357	3
Constant	1678.21				

Multiple R	.96408 (after step 7)
R-Squared	.92944
Adjusted R-Squared	.91491
Standard Error	1.31438

F = 63.981 Significance of F < .001

Table 15

Dependent Variable
Actual Mean Time for Overhaul (ACT_OVRH)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_OVR	400.64225	20.52509	.33	.5986 (25) P=.002	1
PER_HS	-261.7608	-1.72049	.35	-.4489 (39) P=.004	1
PRED_R_I	30.68815	5.61091	.13	.4838 (26) P=.012	1
RET_RTE	-449.2667	-7.44110	.15	-.5511 (35) P=.001	1
USE1	-511.2297	-39.97020	.05	.0921 (69) P=.452	2
MOS9	-513.0197	-16.83993	0	-.0285 (69) P=.816	2
PRED_RPL	-66.7 7068	-12.32817	0	-.0971 (26) P=.637	1
PRED_INS	350.26347	19.62472	0	-.1154 (26) P=.575	1
SYS2	283.84328	17.77961	0	.0301 (69) P=.806	2
PRED_SER	-33.19202	-2.16784	0	-.1951 (25) P=.350	1

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
MN_AFQT	-6.37773	-11.38335	0	.0403 (35) P=.818	1
PRED_TST	73.27359	14.99180	0	.1795 (26) P=.380	1
PRED_ADJ	-217.2246	-15.61476	0	-.1128 (26) P=.583	1
MOS3	172.15076	10.78332	0	-.1508 (69) P=.216	2
SYS8	-152.8321	-9.69397	0	-.0921 (69) P=.452	2
TRAIN_LE	-.98853	-10.00286	0	.1253 (38) P=.454	1
PRED_RPR	-3.24762	-4.18017	0	-.0320 (26) P=.877	1
MOS1	-136.6517	-3.42388	0	-.0160 (69) P=.896	2
PRED_OTH	50.30848	3.92971	0	.1074 (26) P=.601	1
PRED_DPA	.07036	3.32929	0	-.0432 (69) P=.724	2
MOS5	78.49691	2.90251	0	-.0829 (69) P=.498	2
USE_RATE	-7.32E-03	-2.99809	0	.0081 (61) P=.950	2

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
PRED_MTB	-.07440	-2.47709	0	-.0031 (62) P=.981	2
Constant	1236.5560				

Multiple R	.98072 (after step 4)
R-Squared	.96182
Adjusted R-Squared	.95418
Standard Error	1.33802
F = 125.944	Significance of F < .001

Table 16

Dependent Variable
Actual Mean Time to Inspect (ACT_INS)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
SYS5	20.56009	.52180	.16	.4092 (121) P=.000	3
MTL2	6.97537	.27934	.09	.3222 (121) P=.000	3
PRED_RPR	.46456	.29927	.07	.2313 (78) P=.042	2
RET_RTE	-34.85091	-.28889	.07	-.2230 (85) P=.040	2
MOS9	15.60983	.25644	.03	.1582 (121) P=.083	3
PRED_OTH	-5.51516	-.21561	.03	-.0737 (77) P=.524	2
Constant	25.05520				

Multiple R	.70256
R-Squared	.49359
Adjusted R-Squared	.44684
Standard Error	9.28892

F = 10.559 Significance of F < .001

Table 17

Dependent Variable
Actual Mean Time to Adjust (ACT_ADJ)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
RET_RTE	-9.09903	-.47164	.21	-.4716 (75) P=.000	2
Constant	7.99301				

Multiple R	.47164
R-Squared	.22244
Adjusted R-Squared	.20720
Standard Error	1.77841

F = 14.590 Significance of F = .0004

Table 18

Dependent Variable
Actual Annual Maintenance Manhours (ACT_MMH)

Elemental Factors in the Equation

Factor	B	Beta	Accounted Variance	Correlation Information	Certainty Rating
MOS9	2731.4036	.36467	.20	.4649 (145) P=.000	3
RET_RTE	-5564.406	-.37485	.10	-.3443 (107) P=.000	3
TRAIN_LE	3.62414	.14916	.04	.1508 (107) P=.121	3
PRED_SER	706.44852	.18766	.03	.1098 (78) P=.339	2
PRED_OVR	1087.2288	.22654	.02	.4082 (78) P=.000	2
AUTHOR	.12541	.18070	.03	.1575 (129) P=.075	3
Constant	3906.1162				

Multiple R	.62105
R-Squared	.38570
Adjusted R-Squared	.36575
Standard Error	1164.76704

F = 19.338 Significance of F < .001

Table 19

Results for Dependent Variable Actual Mean Time to Inspect (ACT_INS) with Inclusion of Interaction Term

Factor	B	Beta	Accounted Variance
SYS5	-1260.3928	-31.98794	.16
MTL2	590.63982	23.65306	.09
PRED_RPR	94.34908	60.77919	.07
RET_RTE	-12146.252	-100.68497	.07
PRED_OTH	-482.05282	-18.84529	.06
MOS9	.70654	283.95346	.02
MOS3	-1672.04976	-52.41813	.02
MOS7	-3611.32297	-66.83071	.04
MTL1	1177.02741	45.09177	.04
MOS5	-1002.14234	-18.54553	.04
MOS8	-1341.56287	-52.33516	.03
MOS6	-711.31686	-14.45615	.03
MOS2	-2691.78646	-52.33428	.05
PRED_RPL	225.91490	20.87595	.02
PRED_R_I	165.51799	15.14595	.04
PRED_TST	-82.99576	-8.49867	.03
SYS8	693.41442	22.01246	.02
PRED_ADJ	642.92802	23.13009	.02
PRED_MTB	-13.23536	-220.53019	.02
SYS6	9445.11535	183.63392	.12
USE_RATE	.41110	83.79490	.C2
SYS2	-383.88457	-12.03464	0
TRAIN_LE	-43.51903	-220.39552	0

Factor	B	Beta	Accounted Variance
LOM1	-2860.69690	11.93882	0
MOS4	-1586.02465	-29.35078	0
PRED_SER	-593.69149	-19.40628	0
Constant	11066.02579		

Multiple R	.99376	(after step 24)
R-Squared	.98756	
Adjusted R Squared	.98259	
Standard Error	1.64805	

F= 198.50550 Significance of F = .0000

Table 20

Results for Dependent Variable Actual Annual Maintenance Manhours (ACT_MMH) with Inclusion of Interaction Term

Factor	B	Beta	Accounted Variance
MOS9	2555.46813	.34118	.20
RET_RTE	-5774.23866	-.38898	.10
PRED_SER	652.86987	.17343	.06
PRED_OVR	1232.03127	.25672	.02
AUTHOR	.15635	.22528	.03
PRED_TST	210.46198	.17514	.01
Constant	4425.88788		

Multiple R	.68699
R-Squared	.47195
Adjusted R Square	.42245
Standard Error	1167.94908

F= 9.53344 Significance of F = .0000

Table 21

Correlations Among Planned Maintenance Task Times and Actual Maintenance Task Times

	ACT_TST	ACT_INS	ACT_ADJ	ACT_RPL	ACT_R_I	ACT_RPR	ACT_OVR	ACT_SER	ACT_OTH	ACT_MMH
PRED TST	.0089 (78) P=.938	.0147 (78) P=.553	-.0434 (54) P=.755	-.1295 (43) P=.408	.1291 (28) P=.513	-.0155 (95) P=.882	.1795 (26) P=.380	.1536 (80) P=.174	-.1391 (43) P=.374	.1147 (80) P=.311
PRED INS	-.0374 (78) P=.745	-.0682 (78) P=.553	.0543 (54) P=.697	.2167 (43) P=.163	-.0969 (28) P=.624	.1554 (95) P=.133	-.1154 (26) P=.575	.0381 (80) P=.737	-.0241 (43) P=.878	.2605 (80) P=.020
PRED ADJ	-.0638 (78) P=.579	-.0794 (78) P=.489	-.0875 (54) P=.529	-.2119 (43) P=.173	.2346 (28) P=.229	-.0790 (95) P=.447	-.1128 (26) P=.583	.1652 (80) P=.143	-.2369 (43) P=.126	.0388 (80) P=.732
PRED RPL	-.0841 (78) P=.464	.1184 (78) P=.302	-.1082 (54) P=.436	-.2113 (43) P=.174	.2340 (28) P=.231	-.1413 (95) P=.172	-.0971 (26) P=.637	-.0343 (80) P=.762	-.1997 (43) P=.199	-.0230 (80) P=.839
PRED R_I	.0575 (78) P=.617	-.0647 (78) P=.574	-.0353 (54) P=.800	.5615 (43) P=.000	-.0036 (28) P=.986	.0310 (95) P=.766	.4838 (26) P=.012	.0503 (80) P=.658	.4101 (43) P=.006	.0390 (80) P=.731
PRED RPR	.7983 (78) P=.000	.2313 (78) P=.042	.0170 (54) P=.903	-.1045 (43) P=.505	-.0749 (28) P=.705	-.0254 (95) P=.807	-.0320 (26) P=.877	.0475 (80) P=.676	-.0482 (43) P=.759	-.0247 (80) P=.828
PRED OVR	.2344 (76) P=.042	.0173 (76) P=.882	.0246 (53) P=.861	.1132 (42) P=.475	.3041 (26) P=.131	.4332 (93) P=.000	.5986 (25) P=.002	.4326 (78) P=.000	.4412 (42) P=.003	.4082 (78) P=.000

	ACT_ TST	ACT_ INS	ACT_ ADJ	ACT_ RPL	ACT_ R_I	ACT_ RPR	ACT_ OVR	ACT_ SER	ACT_ OTH	ACT_ MMH
PRED SER	.0128 (76) P=.912	-.0786 (76) P=.500	-.0578 (53) P=.681	-.2699 (42) P=.084	.3869 (26) P=.051	-.0100 (93) P=.924	-.1951 (25) P=.350	.1800 (78) P=.115	-.1356 (42) P=.392	.1098 (78) P=.339
PRED OTH	-.0161 (77) P=.890	-.0737 (77) P=.524	.1719 (54) P=.214	.3275 (43) P=.032	.0884 (27) P=.661	.1621 (94) P=.119	.1074 (26) P=.601	.2995 (79) P=.007	.1825 (43) P=.242	.1604 (79) P=.158
PRED DPA	-.0604 (121) P=.510	-.1030 (121) P=.261	-.1129 (119) P=.221	-.1221 (107) P=.210	-.0259 (70) P=.831	-.0837 (159) P=.294	-.0432 (69) P=.724	.0120 (145) P=.886	-.0644 (108) P=.508	.0087 (145) P=.917

Table 22

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Repair (ACT_RPR)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
O & O Plan, Maintenance Concept	LOM1	.38385	.383853	3
Maintenance Profile	PRED_OVR	.38325	.383252	2
Manpower Pool Characteristics, Personnel to be Trained	MN_AFQT	-.21299	-.212993	3

Table 23

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Remove or Install (ACT_R_I)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Maintenance Profile	PRED_SER	.40829	.738741	1
	PRED_OVR	.33045		

Table 24
Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Service (ACT_SERV)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Maintenance Profile	PRED_OVR	.61535	.992372	2
	PRED_TST	.37702		
Maintenance Concept	MTL1	.31010	.310103	3
Training System	TRAIN_LE	-.42497	-.424973	3
MOS,BOIP	MOS1	-.20268	-.202683	3
O & O Plan System	USE3	.27769	.277693	3

Table 25

Metafactor Beta Weights fc r Dependent Variable: Actual Annual Maintenance Manhours (ACT_MMH)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
BOIP, MOS	MOS9	.36467	.364673	3
Training System	TRAIN_LE	.14916	.149163	3
Tasks, Maintenance Profile	PRED_SER	.18766	.414202	2
Availability	AUTHOR	.18070	-.194053	3
	RET_RTE	-.37485		

Table 26

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Replace (ACT_RPL)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Availability	RET-RTE	-417.8538	-417.8538	2
Tasks, Maintenance Profile	PRED_R_I	140.94357	633.24386	3
	PRED_RPL	-249.7842		
	PRED_OTH	72.69970		
	PRED_SER	-110.0355		
	PRED_INS	386.64914		
	PRED-OVR	407.91026		
	PRED_TST	232.66849		
	PRED_RPR	-48.56110		
	PRED_ADJ	-199.2465		
BOIP, MOS	MOS1	-165.5118	-1776.25144	3
	MOS2	-147.2111		
	MOS3	-27.69558		
	MOS4	-261.8896		
	MOS5	-11.78716		
	MOS6	-177.3549		
	MOS7	-303.4164		
	MOS8	-233.3338		
	MOS9	-448.0511		
O & O Plan System	SYS1	-267.9040	-563.2303	3
	SYS8	-295.3263		

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Manpower Pool Character- istics, Personnel to be Trained	MN_AFQT	-115.0990	-160.9436	2
	PER_HS	-45.84460		
System Maintenance Characterist ics	PRED_MTB	-136.4592	-136.4592	3
Availability	AUTHOR	-947.0901	50.67854	2
	PRED_ASS	997.76954		
Training System	TRAIN_LE	-245.9018	-245.9018	2
Maintenance Concept, Maintenance Profile	MTL1	27.09008	26.03138	3
	MTL2	-1.05870		
Maintenance Concept	LOM1	-675.1615	-675.1615	3
OPTEMPO	USE_RATE	-156.3967	-156.3967	2

Table 27

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Test (ACT_TST)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Tasks, Maintenance Profile	PRED_RPR	76.50056	49.38379	2
	PRED_RPL	-27.11677		
Availability	RET_RTE	-205.0936	-210.09113	2
	OPER	-4.99753		
BOIP, MOS	MOS2	-74.81361	-234.70541	3
	MOS3	-33.63780		
	MOS7	-126.2540		
Manpower Pool Characteristics, Personnel to be Trained	MN_AFQT	66.63085	66.63085	2
System Maintenance Characteristics	PRED_MTB	-819.5406	-819.5406	3
Training System	TRAIN_LE	63.46743	63.46743	2
O & O Plan, System	USE1	-571.8572	-558.46955	3
	SYS2	-23.87889		
	SYS3	-308.2026		
	SYS6	536.23794		
	SYS8	-190.7688		

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Maintenance Concept, Maintenance Profile	MTL2	-1.45460	-1.45460	3

Table 28

Metafactor Beta Weights for Dependent Variable: Actual Mean Time for Other Tasks(ACT_OTH)

Metafactor	Elemental Variables	Beta for Elemental Variables	Beta for Metafactor	Certainty Rating for Metafactor
Tasks, Maintenance Profile	PRED_OVR	20.39984	30.24604	1
	PRED_R_I	8.73244		
	PRED_RPL	-13.93719		
	PRED_INS	16.68280		
	PRED_SER	-5.43592		
	PRED_TST	14.94312		
	PRED_ADJ	-13.24649		
	PRED_OTH	5.73179		
	PRED_RPR	-3.62435		
Availability	RET_RTE	-20.33874	-16.66352	2
	PRED_ASS	25.07266		3
	OPER	-21.39744		
O & O Plan, System	SYS1	-12.72814	-59.58839	3
	SYS8	-14.03291		
	USE1	-32.82734		
BOIP, MOS	MOS1	-7.69131	-87.28168	3
	MOS2	-7.22547		
	MOS3	.15843		
	MOS4	-13.83289		
	MOS5	.56880		
	MOS6	-8.78440		
	MOS 7	-15.6353		

Metafactor	Elemental Variables	Beta for Elemental Variables	Beta For Metafactor	Certainty Rating for Metafactor
	MOS8	-13.09179		
	MOS9	-21.75152		
System Maintenance Characteristics	PRED_MTB	-6.62083	-0.56615	3
	PRED_DPA	6.05468		
Manpower Pool Characteristics, Personnel to be Trained	MN_AFQT	-8.08494	-12.08885	2
	PER_HS	-4.00391		
Training System	TRAIN_LE	-11.27271	-11.27271	2
OPTEMPO	USE_RATE	-6.86357	-6.86357	3
Maintenance Concept, Maintenance Profile	MTL2	-2.29027	-4.39979	3
	MTL1	-2.10952		

Table 29

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Overhaul (ACT-OVRH)

MetaFactor	Elemental Factors	Beta For Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Task, Maintenance Profile	PRED_OVR	20.52509	30.39129	1
	PRED_R_I	5.61091		
	PRED_RPL	-12.32817		
	PRED_INS	19.62472		
	PRED_SER	-2.16784		
	PRED_TST	14.99180		
	PRED_ADJ	-15.61476		
	PRED_RPR	-4.18017		
	PRED_OTH	3.92971		
Manpower Pool Characteristics, Personnel to be Trained	PER_HS	-1.72049	-13.30384	1
	MN_AFQT	-11.58335		
Availability	RET_RTE	-7.44110	-7.44110	1
O & O Plan System	USE1	-39.97020	-31.88456	2
	SYS2	17.77961		
	SYS8	-9.69397		
BOIP, MOS	MOS1	-3.42388	-6.57798	2
	MOS3	10.78332		
	MOS5	2.90251		
	MOS9	-16.83993		

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta For Metafactor	Certainty Rating for Metafactor
Training System	TRAIN_LE	-10.00286	-10.00286	1
System Maintenance Characteristics	PRED_DPA	3.32929	0.8522	2
	PRED_MTB	-2.47709		
OPTEMPO	USE_RATE	-2.99809	-2.99809	2

Table 30

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Inspect (ACT_INS)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
O & O Plan, System	SYS5	.52180	.52180	3
Maintenance Concept, Maintenancc Profile	MTL2	.27934	.27934	3
Tasks, Maintenance Profile	PRED_RPR	.29927	.08366	2
	PRED_OTH	-.21561		
Availability	RET_RTE	-.28889	-.28889	2
BOIP, MOS	MOS9	.25644	.25644	3

Table 31

Metafactor Beta Weights for Dependent Variable: Actual Mean Time to Adjust (ACT_ADJ)

Metafactor	Elemental Factors	Beta for Elemental Factors	Beta for Metafactor	Certainty Rating for Metafactor
Availability	RET_RTE	-.47164	-.47164	2

Table 32

Mean Certainty Score for Regression Equations

Dependent Measure	Mean Certainty Rating
ACT_TST (Actual mean time to test equipment)	2.69
ACT_INS (Actual mean time to inspect equipment)	2.50
ACT_ADJ (Actual mean time to make adjustments to equipment	2.00
ACT_R_I (Actual mean time to remove or install equipment)	1.00
ACT_RPL (Actual mean time to replace equipment)	2.19
ACT_RPL (Actual mean time to repair equipment)	2.67
ACT_OVRH (Actual mean time to overhaul equipment)	1.43
ACT_SERV (Actual mean time to service equipment)	2.67
ACT_OTH (Actual mean time to perform maintenance tasks not covered by other categories)	2.26
ACT_MMH (Actual annual maintenance manhours for MOS working on specific system)	2.67

Table 33

Planned and Actual MOSs for System: M2A1

Planning Documents Data	SDC Data
27E	27E
31V	31E
41C	31V
44B	41C
44E	44B
45B	44E
45K	45B
45T	45D
52C	45E
63G	45G
63H	45K
63T	45T
	52C
	52D
	63G
	63H
	63T

Table 34

Planned and Actual MOSs for System: IHawk

Planning Documents Data	SDC Data
24C	24C
24E	24G
24G	24H
24H	24J
24J	24K
24K	24L
24L	25L
24R	27H
25L	
27H	
27J	
31M	
52C	
52D	
63B	
63G	
63H	
63W	

Table 35

Planned and Actual MOSs for System: M1038 HMMWV

Planning Documents Data	SDC Data
35H	21G
44B	31K
44E	31V
63B	35H
63G	43M
63W	44B
	44E
	45D
	52C
	52D
	62B
	63B
	63D
	63G
	63H
	63J
	63S
	63T
	68G

Table 36

Planned and Actual MOSs for System: UH-60A

Planning Documents Data	SDC Data
66T	26E
67T	35K/68N*
68B	35M/68Q*
68D	35P/68P*
68F	68B
68G	68D
68H	68F
68J	68G
68N	68H
68Q	68J
68R	68M
26K	66T
67H	35R/68T*
67T	
92C	

* MOS designators recently changed

Table 37

Planned and Actual MOSs for System: CH-47D

Planning Documents Data	SDC Data
67U	68B
68B	68D
68D	68F
68F	68H
68H	68G
68G	35K/68N*
35K/68N*	68J
	68K
	68M
	67W
	35M/68Q*
	35R/68R*
	26E

* MOS designators recently changed

Table 38

Planned and Actual MOSs for System: M977 HEMTT

Planning Documents Data	SDC Data
31E	24T
31V	44B
35B	44E
35E	52D
45B	62B
63G	63B
63S	63D
63W	63E
76Y	63G
	63H
	63T
	63W
	68H

Table 39

Planned and Actual MOSs for System: M1A1

Planning Documents Data	SDC Data
29E	31V
31V	44B
35H	44E
44E	45B
41C	45E
44B	45G
45E	45K
45G	45N
45K	45T
63E	52C
63H	52G
	54B
	63D
	63E
	63G
	63H
	63N
	63T
	63W
	65E

Table 40

Planned and Actual MOSs for System: M198

Planning Documents Data	SDC Data
45L	45L
	35K/68N*
	41C
	41K
	44B
	44C
	44E
	45B
	45D
	45G
	45K
	45Z
	55D
	63B
	63D
	63H

* MOS designators recently changed

Table 41

Planned and Actual MOSs for System: VULCAN

Planning Documents Data	SDC Data
24M	24M
27F	27F
41C	27M
45L	52D

Table 42

MOS Planning Versus Actual Mos Utilization

System	Number of Planned MOSs	Number of Actual MOSs	Overlap Between Planned and Actual	Percent Overlap
M1A1	11	25	9	82% of planned
M198	11	9	1	9% of planned
IHAWK	18	8	8	44% of planned
M2A1	12	18	12	100% of planned
M1038	6	25	6	100% of planned
UH-60A	15	15	9	60% of planned
CH-47D	7	15	6	86% of planned
M977	9	15	3	33% of planned
VULCAN	4	4	2	50% of planned

Table 43

Equations for RIT-TOM Factor Spreadsheets

Dependent Measure	Equation	Equation Statistics
Actual Time to Inspect	(10.4 * MTL2)	MULTIPLE R = .83
	-(27.4 * SYS1)	R-SQUARED = .69
	-(14.5 * MOS2)	ADJUSTED
	-(5.9 * MOS9)	R-SQUARED = .58
	-(17.1 * MOS5)	
	-(10.2 * MOS1)	F = 6.03 P < .001
	-(15.5 * MOS4)	
	-(52.8 * MOS7)	
	-(24.1 * SYS6)	
	-(27.0 * MOS6)	
	-(4.6 * SYS5)	
	-(23.4 * SYS7)	
	+(.2 * MN_AFQT)	
	-(23.3 * SYS3)	
	+(.0007 * AUTHOR)	
	-(26.3 * MOS3)	
	-(29.5 * SYS2)	
	-(52.0 * PER_HS)	
	+(2.9 * MTL1)	
	+(.03 * TRAIN_LE)	
	-(21.0 * SYS8)	
	-(16.3 * MOS8)	
	-(131.0 * RET_RTE)	
	+168.1	

Dependent Measure	Equation	Equation Statistics
Actual Time to Test	(1.8 * MTL2) -(7.7 * SYS1) -(.27 * MOS2) -(4.4 * MOS9) -(4.0 * MOS5) -(4.8 * MOS1) -(5.0 * MOS4) -(16.9 * MOS7) -(8.0 * SYS6) -(7.3 * MOS6) -(7.8 * SYS5) -(8.6 * SYS7) +(.08 * MN_AFQT) -(6.1 * SYS3) +(.0002 * AUTHOR) -(7.5 * MOS3) -(9.3 * SYS2) -(23.3 * PER_HS) +(.8 * MTL1) +(.007 * TRAIN_LE) -(6.1 * SYS8) -(4.0 * MOS8) -(47.6 * RET_RTE) +63.1	MULTIPLE R = .72 R-SQUARED = .52 ADJUSTED R-SQUARED = .34 F = 2.89 P < .001
Actual Time to Remove or Install	(.3 * MTL2) -(.01 * SYS1) -(1.2 * MOS2) +(.13 * MOS9) -(.18 * MOS5) -(.8 * MOS1) -(1.6 * MOS7) -(.1 * MOS6) -(.2 * SYS7) -(.0001 * AUTHOR) -(.36 * SYS8) +(.1 * MN_AFQT +(.4 * MOS3) -(1.5 * SYS2) +(.3 * USE6) -(10.3 * PER_HS) -(.2 * MTL1) -(.003 * TRAIN_LE) -(.1 * MOS8) -(4.0 * RET_RTE) +9.9	MULTIPLE R = .47 R-SQUARED = .22 ADJUSTED R-SQUARED =-.81 F = .21 P < 1.0

Dependent Measure	Equation	Equation Statistics
Actual Time to Replace	(.9 * MTL2) -(1.8 * SYS1) -(1.7 * MOS2) +(1.6 * MOS9) -(3.4 * MOS5) +(7.0 * MOS1) -(4.2 * MOS4) +(6.8 * MOS7) -(5.8 * MOS6) -(.0008 * AUTHOR) -(3.6 * SYS8) -(.2 * MN_AFQT) -(4.6 * MOS3) -(.5 * SYS2) -(14.7 * PER_HS) +(1.0 * MTL1) +(.03 * TRAIN_LE) -(16.4 * RET_RTE) -(1.7 * MOS8) +40.6	MULTIPLE R = .82 R-SQUARED = .67 ADJUSTED R-SQUARED = .53 F = 4.58 P < .001
Actual Time to Adjust	(.4 * MTL2) -(2.6 * SYS1) -(.4 * MOS2) -(1.0 * MOS9) -(.2 * MOS5) -(.5 * MOS1) -(.3 * MOS4) -(4.6 * MOS7) -(.6 * SYS6) -(1.4 * MOS6) +(.01 * MN_AFQT) +(.1 * SYS3) +(.0001 * AUTHOR) -(2.4 * SYS8) -(.6 * MOS3) -(2.9 * SYS2) -(4.2 * PER_HS) +(.2 * MTL1) -(.004 * TRAIN_LE) -(2.30 * USE6) -(18.0 * RET_RTE) -(1.1 * MOS*) -(2.0 * USE3) +21.0	MULTIPLE R = .61 R-SQUARED = .37 ADJUSTED R-SQUARED = .08 F = 1.27 P < .001

Dependent Measure	Equation	Equation Statistics
Actual Time to Repair	(1.2 * MTL2) +(6.7 * SYS1) +(1.3 * MOS2) +(7.7 * MOS9) -(1.1 * MOS5) +(3.5 * MOS1) +(1.5 * MOS4) +(5.4 * MOS7) +(1.0 * SYS6) -(.6 * MOS6) +(2.1 * SYS5) +(1.6 * SYS7) -(.2 * MN_AFQT) +(1.8 * SYS3) -(.0003 * AUTHOR) +(.2 * MOS3) +(7.7 * SYS2) +(9.7 * PER_HS) -(.7 * MTL1) +(.03 * TRAIN_LE) +(2.4 * SYS8) +(.7 * MOS8) +(9.4 * RET_RTE) -12.4	MULTIPLE R = .63 R-SQUARED = .40 ADJUSTED R-SQUARED = .24 F = 2.43 P < .002
Actual Time to Service	(1.3 * MTL2) -(5.6 * SYS1) +(.4 * MOS2) +(2.5 * MOS9) +(2.8 * MOS5) -(3.4 * MOS1) +(2.0 * MOS4) -(4.0 * MOS7) -(4.7 * SYS6) -(.9 * MOS6) -(3.6 * SYS5) -(5.3 * SYS7) +(.1 * MN_AFQT) -(3.9 * SYS3) +(.0004 * AUTHOR) -(.9 * MOS3) -(6.3 * SYS2) +(13.3 * PER_HS) +(2.0 * MTL1) -(.03 * TRAIN_LE) -(5.3 * SYS8) -(.04 * MOS8) -(20.3 * RET_RTE) +5.5	MULTIPLE R = .63 R-SQUARED = .40 ADJUSTED R-SQUARED = .23 F = 2.35 P < .003

Dependent Measure	Equation	Equation Statistics
Actual Time to	(1.7 * MTL2)	MULTIPLE R = .88
Overhaul	-(6.2 * SYS1)	R-SQUARED = .77
	-(9.4 * MOS2)	ADJUSTED
	-(1.6 * MOS9)	R-SQUARED = .51
	-(5.1 * MOS5)	
	+(1.7 * MOS1)	F = 2.97 P < .02
	-(1.2 * MOS7)	
	-(7.3 * MOS6)	
	-(.0008 * AUTHOR)	
	-(3.3 * SYS8)	
	+(.04 * MN_AFQT)	
	-(7.5 * MOS3)	
	-(7.9 * SYS2)	
	-(52.1 * PER_HS)	
	-(.3 * MTL1)	
	+(.04 * TRAIN_LE)	
	-(3.3 * MOS8)	
	-(44.0 * RET_RTE)	
	+80.8	
Actual Time to Perform	(.3 * MTL2)	MULTIPLE R = .48
Other Tasks	-(4.4 * SYS1)	R-SQUARED = .23
	-(4.1 * MOS2)	ADJUSTED
	-(2.5 * MOS9)	R-SQUARED = -.12
	-(.3 * MOS5)	
	-(3.8 * MOS1)	F = .65 P < .9
	-(2.9 * MOS4)	
	-(11.5 * MOS7)	
	-(4.8 * MOS6)	
	+(.0002 * AUTHOR)	
	-(1.4 * SYS8)	
	+(.05 * MN_AFQT)	
	-(3.1 * MOS3)	
	-(3.1 * SYS2)	
	+(10.9 * PER_HS)	
	+(1.9 * MTL1)	
	-(.006 * TRAIN_LE)	
	-(39.3 * RET_RTE)	
	-3.3 * MOS8)	
	+23.1	

Dependent Measure	Equation	Equation Statistics
Actual Annual Maintenance Manhours	(614.3 * MTL2) -(2347.9 * SYS1) -(2360.4 * MOS2) +(1127.8 * MOS9) -(1946.7 * MOS5) -(2749.4 * MOS1) -(1731.2 * MOS4) -(5935.4 * MOS7) -(1668.6 * SYS6) -(2400.7 * MOS6) -(2494.8 * SYS5) -(1934.2 * SYS7) +(42.3 * MN_AFQT) -(2365.4 * SYS3) +(.2 * AUTHOR) -(3221.2 * MOS3) -(2507.6 * SYS2) -(2908.3 * PER_HS) +(603.4 * MTL1) +(1.7 * TRAIN_LE) -(2205.5 * SYS8) -(1997 * MOS8) -(15498.8 * RET_RTE) +15751.6	MULTIPLE R = .78 R-SQUARED = .60 ADJUSTED R-SQUARED = .49 F = 5.31 P < .001

Dependent Measure	Equation	Equation Statistics
Number of Authorized Personnel	(8511 * SYS1) -(1191 * MTL2) +(1386 * MOS2) +(2663 * MOS9) -(483 * MOS5) +(5862 * MOS1) +(1179 * MOS4) +(13128 * MOS7) +(3508 * MOS6) +(7267 * SYS8) -(165 * MN_AFQT) +(4167 * MOS3) +(9739 * SYS2) -(378 * PER_HS) -(533 * MTL1) +(31 * TRAIN_LE) +(37146 * RET_RTE) +(2726 * MOS8) +(370 * ACT_SERV) +(1196 * SYS3) +(113 * SYS6) +(33 * ACT_ADJ) +(116 * ACT_TST) -(208 * ACT_RPR) +(97 * ACT_INS) +(7774 * USE6) +(5400 * USE3) -31241	MULTIPLE R = .79 R-SQUARED = .63 ADJUSTED R-SQUARED = .40 F = 2.78 P < .01

Dependent Measure	Equation	Equation Statistics
Mean AFQT Scores	-(7.6 * MTL2)	MULTIPLE R = .90
	+(39.8 * SYS1)	R-SQUARED = .80
	+(12.3 * MOS2)	ADJUSTED
	+(1.9 * ACT_SERV)	R-SQUARED = .68
	+(2.1 * MOS5)	
	+(47.1 * PER_HS)	F = 6.72 P < .001
	+(27.4 * MOS1)	
	+(9.2 * SYS3)	
	-(.002 * AUTH)	
	+(17.2 * MOS6)	
	+(11.2 * MOS9)	
	-(1.9 * SYS6)	
	+(9.5 * MOS4)	
	-(.2 * ACT_ADJ)	
	+(60.5 * MOS7)	
	+(.6 * ACT_TST)	
	+(31.5 * SYS8)	
	-(1.2 * ACT_RPR)	
	+(21.7 * MOS3)	
	+(.5 * ACT_INS)	
	+(47.9 * SYS2)	
	-(6.7 * MTL1)	
	+(.13 * TRAIN_LE)	
	+(30.3 * USE6)	
	+(18.9 * USE3)	
	+(12.7 * MOS8)	
	+(166.1 * RET_RTE)	
	-167.6	

Dependent Measure	Equation	Equation Statistics
Retention Rate	(.04 * MTL2)	MULTIPLE R = .98
	-(.2 * SYS1)	R-SQUARED = .96
	-(.07 * MOS2)	ADJUSTED
	-(.08 * MOS9)	R-SQUARED = .94
	-(.04 * MOS5)	
	-(.11 * MOS1)	F = 44.11 P < .001
	-(.08 * MOS4)	
	-(.35 * MOS7)	
	+(.002 * SYS6)	
	-(.14 * MOS6)	
	+(.002 * MN_AFQT)	
	-(.04 * SYS3)	
	+(.000008 * AUTHOR)	
	-(.14 * MOS3)	
	-(.23 * SYS2)	
	-(.18 * PER_HS)	
	+(.03 * MTL1)	
	-(.0002 * TRAIN_LE)	
	-(.15 * SYS8)	
	-(.08 * MOS8)	
	-(.004 * ACT_SERV)	
	-(.003 * ACT_ADJ)	
	-(.004 * ACT_TST)	
	+(.004 * ACT_RPR)	
	-(.003 * ACT_INS)	
	-(.2 * USE6)	
	-(.1 * USE3)	
	+1	

Dependent Measure	Equation	Equation Statistics
Training Length	(6.9 * MTL2) -(129.6 * SYS1) +(20 * MOS2) -(3.6 * MOS9) +(96.2 * MOS5) -(99.5 * MOS1) -(66.5 * MOS7) +(9.7 * MOS6) +(.01 * AUTHOR) -(109 * SYS8) +(3 * MN_AFQT +(9.9 * MOS3) -(146.4 * SYS2) -(105.6 * USE6) +(262 * PER_HS) +(19.7 * MTL1) -(87.8 * USE3) +(4.4 * MOS8) -(356.8 * RET_RTE) -(8.8 * ACT_SERV) +(6.4 * SYS3) +(22.5 * SYS6) +(34.1 * MOS4) +(1.7 * ACT_ADJ) +(1.1 * ACT_TST) -(.4 * ACT_INS) +69.3	MULTIPLE R = .92 R-SQUARED = .84 ADJUSTED R-SQUARED = .75 F = 9.18 P < .001

Table 44

RIT-TOM Test: Prediction of Task Times, Data Entered

Factor	Data Entered
System Type	6
System Use	6
Number of Levels of Maintenance	4
Maintenance Level	1
MOS Type	8
Mean AFQT Score	49
Percent High School Graduates	.86
Retention Rate	.76
Number Authorized	16872
Length of Basic Skills Course	252

Table 45

Actual Maintenance Task Times Versus RIT-TOM Predictions

Task	Actual Task Time	RIT-TOM Predicted	Difference
Time to Inspect	.07	15.4	15.3
Time to Test	.22	4.8	4.6
Time to Remove/Install	No Data	1.9	1.9
Time to Replace	No Data	- .9	- .9
Time to Repair	.93	-3.2	-2.7
Time to Overhaul	No Data	-2.5	-2.5
Time to Adjust	No Data	2.19	2.19
Time to Service	3.26	2.9	-.36
Time for Other Tasks	No Data	5.7	5.7

Table 46

RIT-TOM Test: Prediction of AMMH, Data Entered

Factor	Data Entered
System Type	6
System Use	6
Number of Levels of Maintenance	4
Maintenance Level	2
MOS Type	2
Mean AFQT Score	60
Percent High School Graduates	.88
Retention Rate	.79
Number Authorized	350
Length of Basic Skills Course	129

Table 47

RIT-TOM Test: Prediction of Mean AFQT, Data Entered

Factor	Data Entered
System Type	6
System Use	6
Number of Levels of Maintenance	4
Maintenance Level	2
MOS Type	8
Percent High School Graduates	.90
Retention Rate	.77
Number Authorized	4053
Length of Basic Skills Course	112
Time to Inspect	0
Time to Test	.20
Time to remove/Install	0
Time to Replace	0
Time to Repair	.32
Time to Adjust	0
Time to Overhaul	0
Time to Service	0
Time for Other Tasks	0

APPENDIX F

RIT-TOM USER'S GUIDE

RIT-TOM USER'S GUIDE

The Requirements Integrated Trade-off TOol for Maintenance (RIT-TOM) is a software product designed to allow its user to perform "what-if" analyses based on various manpower, personnel and training factors that impact maintenance performance. RIT-TOM is based on LOTUS 1-2-3, and this user's guide is written with the assumption that the users of this tool will be familiar with LOTUS to the extent that they can call up a file, enter data, and manipulate those data.

RIT-TOM is comprised of five LOTUS 1-2-3, Version 2.01 files, each containing one spreadsheet. These files are:

1. MPTPRED.WK1: This file can be used to predict maintenance performance times for classes of MOSs at different levels of maintenance, given a particular type of equipment.

2. AFQT.WK1: This file can be used to predict mean AFQT scores for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment.

3. AUTHOR.WK1: This file can be used to predict the number of personnel to be authorized for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment.

4. RETRTE.WK1: This file can be used to predict the retention rate for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment.

5. TRAIN.WK1: This file can be used to predict the length of the basic skills course in days for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment.

Depending on the question you wish to answer, you will select one of these files. Each spreadsheet is slightly different, but they all require you to input similar types of information. These spreadsheets were developed based on multiple regression equations as described in Evans, Kapp, and Roth (1990). In the following sections of this guide, you will find detailed descriptions of the data to be entered into each spreadsheet.

MPTPRED.WK1

This file can be used to predict maintenance performance times for classes of MOSs at different levels of maintenance, given a particular type of system. The use of this spreadsheet assumes that you are asking questions about a specific type of system and a specific MOS maintaining the system at a particular level of maintenance.

To use this spreadsheet, call it up in LOTUS 1-2-3. The spreadsheet is designed to allow you to input data for one case per row. This spreadsheet is set up to support the analysis of five cases, each taking up one row. It contains the following fields requiring data entry as described:

1. SYSTEM TYPE. Enter a number from 1 to 9 to designate the system type. Table 1 shows how the numbers relate to each system type.

2. SYSTEM USE. Enter a number from 1 to 7 to indicate the environment in which the system is usually used. Table 2 shows the relationship between the numbers and system use.

3. NO. LEVELS OF MAINTENANCE. Enter 1 to indicate three levels of maintenance (e.g., AVUM, AVIM, and Depot) or 2 for four levels (Unit/Battery, Direct Support, General Support, and Depot).

4. MAINTENANCE LEVEL. Enter 1 to indicate unit level maintenance as focus of analysis (Unit, Battery, or AVUM), 2 for Direct Support or AVIM, or 3 for General Support.

5. MOS TYPE. Classify the MOS for which you are performing the analysis by the type of repairs made or systems repaired. Enter a number from 1 to 10 to designate the type of system/subsystem maintained by the MOS at the maintenance level designated. Table 3 indicates the relationship between the MOS designator numbers and the MOS task focus.

6. MEAN AFQT SCORE. Enter the mean AFQT score for the MOS type under examination. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher AFQT scores on the outcome.

7. PROPORTION HIGH SCHOOL GRADS. Enter the proportion of persons in the target MOS who have graduated from high school. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher proportions of high school graduates on the outcome.

8. RETENTION RATE. Enter the proportion of persons in the target MOS who are retained after their first tour of duty. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may

use made-up data to see the impact of lower or higher retention rates on the outcome.

9. NUMBER AUTHORIZED. Enter the number of authorized personnel of the target MOS. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher authorizations on the outcome.

10. LENGTH OF BASIC SKILLS COURSE. Enter the length of the basic skills course for the MOS in days. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of longer or shorter courses on the outcome.

Once you have entered the data as described above, hit the calculate key (F9). LOTUS will calculate values for the following fields:

1. TIME TO INSPECT. This is an estimate of the mean time to inspect a fielded system or its components at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

2. TIME TO TEST. This is an estimate of the mean time to test a fielded system or its components at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

3. REMOVE/INSTALL TIME. This is an estimate of the mean time to remove or install a system's component at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

4. TIME TO REPLACE. This is an estimate of the mean time to replace a system's component at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

5. TIME TO REPAIR. This is an estimate of the mean time to repair the system or one of its components at the maintenance level of interest and by the target MOS given the specified MPT factor values.

6. TIME TO OVERHAUL. This is an estimate of the mean time to overhaul the system or one of its components at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

7. TIME TO SERVICE. This is an estimate of the mean time to service a system or its components at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

8. TIME TO ADJUST. This is an estimate of the mean time to adjust a system's component at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

9. TIME FOR OTHER TASKS. This is an estimate of the mean time to perform other tasks at the maintenance level of interest and by the target MOS, given the specified MPT factor values.

10. AMMH (ANNUAL MAINTENANCE MANHOURS). This is an estimate of the number of actual annual maintenance manhours which will be expended by personnel of the target MOS at the selected maintenance level for the designated system type.

AFQT.WK1

This file can be used to predict mean AFQT scores for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment. This spreadsheet is set up so that you can enter data for up to five cases. The data fields for which you must enter data are:

1. TIME TO INSPECT. Enter an estimate of the mean time for inspection for the system and its components Express this value in hours and tenths of hours (e.g., 1.5 means one and one-half hours).

2. TIME TO TEST. Enter an estimate of the mean time for testing the system and its components.

3. TIME TO REPLACE. Enter an estimate of the mean time to replace a system component.

4. TIME TO REMOVE/INSTALL. Enter an estimate of the mean time to remove or install a system component.

5. TIME TO REPAIR. Enter an estimate of the mean time to repair the system or its components.

6. TIME TO OVERHAUL. Enter an estimate of the mean time to overhaul the system or its components.

7. TIME TO SERVICE. Enter an estimate of the mean time to service the system or its components.

8. TIME TO ADJUST. Enter an estimate of the mean time to adjust the system or its components.

9. TIME FOR OTHER TASKS. Enter an estimate of the mean time to perform other tasks for the system or its components.

10. SYSTEM TYPE. Enter a number from 1 to 9 to designate the system type. Table 1 shows how the numbers relate to each system type.

11. SYSTEM USE. Enter a number from 1 to 7 to indicate the environment in which the system is usually used. Table 2 shows the relationship between the numbers and system use.

12. NO. LEVELS OF MAINTENANCE. Enter 1 to indicate three levels of maintenance (e.g., AVUM, AVIM, and Depot) or 2 for four levels (Unit, Direct Support, General Support, and Depot).

13. MAINTENANCE LEVEL. Enter 1 to indicate unit level maintenance as focus of analysis (Unit, Battery, or AVUM), 2 for Direct Support or AVIM, or 3 for General Support.

14. MOS TYPE. Classify the MOS for which you are performing the analysis by the type of repairs made or systems repaired. Enter a number from 1 to 10 to designate the type of system/subsystem maintained by the MOS at the maintenance level designated. Table 3 indicates the relationship between the MOS designator numbers and the MOS task focus.

15. PROPORTION HIGH SCHOOL GRADS. Enter the proportion of persons in the target MOS who have graduated from high school. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher proportions of high school graduates on the outcome.

16. RETENTION RATE. Enter the proportion of persons in the target MOS who are retained after their first tour of duty. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher retention rates on the outcome.

17. NUMBER AUTHORIZED. Enter the number of authorized personnel of the target MOS. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher authorizations on the outcome.

18. LENGTH OF BASIC SKILLS COURSE. Enter the length of the basic skills course for the MOS in days. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of longer or shorter courses on the outcome.

After you have entered the above data, press F9. The value in the column "PREDICTED AFQT SCORE" will change. It will contain an estimate of the AFQT score for target personnel performing the selected maintenance task.

AUTHOR.WK1

This file can be used to predict the number of personnel to be authorized for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment. This spreadsheet is set up so that you can enter data for up to five cases. The data fields for which you must enter data are:

1. TASK TIME. Enter an estimate of the mean time for inspection for the system and its components Express this value in hours and tenths of hours (e.g., 1.5 means one and one-half hours).

2. TIME TO TEST. Enter an estimate of the mean time for testing the system and its components.

3. TIME TO REPLACE. Enter an estimate of the mean time to replace a system component.

4. TIME TO REMOVE/INSTALL. Enter an estimate of the mean time to remove or install a system component.

5. TIME TO REPAIR. Enter an estimate of the mean time to repair the system or its components.

6. TIME TO OVERHAUL. Enter an estimate of the mean time to overhaul the system or its components.

7. TIME TO SERVICE. Enter an estimate of the mean time to service the system or its components.

8. TIME TO ADJUST. Enter an estimate of the mean time to adjust the system or its components.

9. TIME FOR OTHER TASKS. Enter an estimate of the mean time to perform other tasks for the system or its components.

10. SYSTEM TYPE. Enter a number from 1 to 9 to designate the system type. Table 1 shows how the numbers relate to each system type.

11. SYSTEM USE. Enter a number from 1 to 7 to indicate the environment in which the system is usually used. Table 2 shows the relationship between the numbers and system use.

12. NO. LEVELS OF MAINTENANCE. Enter 1 to indicate three levels of maintenance (e.g., AVUM, AVIM, and Depot) or 2 for four levels (Unit, Direct Support, General Support, and Depot).

13. MAINTENANCE LEVEL. Enter 1 to indicate unit level maintenance as focus of analysis (Unit, Battery, or AVUM), 2 for Direct Support or AVIM, or 3 for General Support.

14. MOS TYPE. Classify the MOS for which you are performing the analysis by the type of repairs made or systems repaired. Enter a number from 1 to 10 to designate the type of system/subsystem maintained by the MOS at the maintenance level designated. Table 3 indicates the relationship between the MOS designator numbers and the MOS task focus.

15. MEAN AFQT SCORE. Enter the mean AFQT score for the MOS type under examination. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher AFQT scores on the outcome.

16. PROPORTION HIGH SCHOOL GRADS. Enter the proportion of persons in the target MOS who have graduated from high school. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher proportions of high school graduates on the outcome.

17. RETENTION RATE. Enter the proportion of persons in the target MOS who are retained after their first tour of duty. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher retention rates on the outcome.

18. LENGTH OF BASIC SKILLS COURSE. Enter the length of the basic skills course for the MOS in days. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of longer or shorter courses on the outcome.

After you have entered the above data, press F9. The value in the column "PREDICTED NUMBER AUTHORIZED" will change. It will contain an estimate of the number of target personnel performing the selected maintenance task likely to be authorized at the indicated maintenance level for the system.

RETRTE.WK1

This file can be used to predict the retention rate for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment. This spreadsheet is set up so that you can enter data for up to five cases. The data fields for which you must enter data are:

1. TIME TO INSPECT. Enter an estimate of the mean time for inspection for system and its components Express this value in hours and tenths of hours (e.g., 1.5 means one and one-half hours).

2. TIME TO TEST. Enter an estimate of the mean time for testing the system and its components.

3. TIME TO REPLACE. Enter an estimate of the mean time to replace a system component.

4. TIME TO REMOVE/INSTALL. Enter an estimate of the mean time to remove or install a system component.

5. TIME TO REPAIR. Enter an estimate of the mean time to repair the system or its components.

6. TIME TO OVERHAUL. Enter an estimate of the mean time to overhaul the system or its components.

7. TIME TO SERVICE. Enter an estimate of the mean time to service the system or its components.

8. TIME TO ADJUST. Enter an estimate of the mean time to adjust the system or its components.

9. TIME FOR OTHER TASKS. Enter an estimate of the mean time to perform other tasks for the system or its components.

10. SYSTEM TYPE. Enter a number from 1 to 9 to designate the system type. Table 1 shows how the numbers relate to each system type.

11. SYSTEM USE. Enter a number from 1 to 7 to indicate the environment in which the system is usually used. Table 2 shows the relationship between the numbers and system use.

12. NO. LEVELS OF MAINTENANCE. Enter 1 to indicate three levels of maintenance (e.g., AVUM, AVIM, and Depot) or 2 for four levels (Unit, Direct Support, General Support, and Depot).

13. MAINTENANCE LEVEL. Enter 1 to indicate unit level maintenance as focus of analysis (Unit, Battery, or AVUM), 2 for Direct Support or AVIM, or 3 for General Support.

14. MOS TYPE. Classify the MOS for which you are performing the analysis by the type of repairs made or systems repaired. Enter a number from 1 to 10 to designate the type of system/subsystem maintained by the MOS at the maintenance level designated. Table 3 indicates the relationship between the MOS designator numbers and the MOS task focus.

15. MEAN AFQT SCORE. Enter the mean AFQT score for the MOS type under examination. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher AFQT scores on the outcome.

16. PROPORTION HIGH SCHOOL GRADS. Enter the proportion of persons in the target MOS who have graduated from high school. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher proportions of high school graduates on the outcome.

17. NUMBER AUTHORIZED. Enter the number of authorized personnel of the target MOS. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher authorizations on the outcome.

18. LENGTH OF BASIC SKILLS COURSE. Enter the length of the basic skills course for the MOS in days. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of longer or shorter courses on the outcome.

After you have entered the above data, press F9. The value in the column "PREDICTED RETENTION RATE" will change. It will contain an estimate of the proportion of target personnel performing the selected maintenance task for the system at the indicated maintenance level who will be retained from their first term of duty to their second.

TRAIN.WK1

This file can be used to predict the length of the basic skills course in days for classes of MOSs performing maintenance tasks at different levels of maintenance, given a particular type of equipment. This spreadsheet is set up so that you can enter data for up to five cases. The data fields for which you must enter data are:

1. TIME TO INSPECT. Enter an estimate of the mean time for inspection for system and its components Express this value in hours and tenths of hours (e.g., 1.5 means one and one-half hours).

2. TIME TO TEST. Enter an estimate of the mean time for testing the system and its components.

3. TIME TO REPLACE. Enter an estimate of the mean time to replace a system component.

4. TIME TO REMOVE/INSTALL. Enter an estimate of the mean time to remove or install a system component.

5. TIME TO REPAIR. Enter an estimate of the mean time to repair the system or its components.

6. TIME TO OVERHAUL. Enter an estimate of the mean time to overhaul the system or its components.

7. TIME TO SERVICE. Enter an estimate of the mean time to service the system or its components.

8. TIME TO ADJUST. Enter an estimate of the mean time to adjust the system or its components.

9. TIME FOR OTHER TASKS. Enter an estimate of the mean time to perform other tasks for the system or its components.

10. SYSTEM TYPE. Enter a number from 1 to 9 to designate the system type. Table 1 shows how the numbers relate to each system type.

11. SYSTEM USE. Enter a number from 1 to 7 to indicate the environment in which the system is usually used. Table 2 shows the relationship between the numbers and system use.

12. NO. LEVELS OF MAINTENANCE. Enter 1 to indicate three levels of maintenance (e.g., AVUM, AVIM, and Depot) or 2 for four levels (Unit, Direct Support, General Support, and Depot).

13. MAINTENANCE LEVEL. Enter 1 to indicate unit level maintenance as focus of analysis (Unit, Battery, or AVUM), 2 for Direct Support or AVIM, or 3 for General Support.

14. MOS TYPE. Classify the MOS for which you are performing the analysis by the type of repairs made or systems repaired. Enter a number from 1 to 10 to designate the type of system/subsystem maintained by the MOS at the maintenance level designated. Table 3 indicates the relationship between the MOS designator numbers and the MOS task focus.

15. MEAN AFQT SCORE. Enter the mean AFQT score for the MOS type under examination. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher AFQT scores on the outcome.

16. PROPORTION HIGH SCHOOL GRADS. Enter the proportion of persons in the target MOS who have graduated from high school. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher proportions of high school graduates on the outcome.

17. RETENTION RATE. Enter the proportion of persons in the target MOS who are retained after their first tour of duty. This value should be a number between .00 and 1.00. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher retention rates on the outcome.

18. NUMBER AUTHORIZED. Enter the number of authorized personnel of the target MOS. This type of data is available on FOOTPRINT reports available for each MOS or you may use made-up data to see the impact of lower or higher authorizations on the outcome.

After you have entered the above data, press F9. The value in the column "PREDICTED LENGTH OF TRAINING" will change. It will contain an estimate of the number of days in the basic skills course for the target personnel performing the selected maintenance task on the system at the indicated level of maintenance.

Table 1

System Designator Numbers and Definitions for SYSTEM Type

System Designator Number	System Designator Definition
1	Transport Helicopter
2	Scout Helicopter
3	Tank
4	Armored Personnel Carrier
5	Fighting Vehicle - Tracked
6	Light Truck
7	Heavy Truck
8	Big Gun/Air Defense Gun
9	Missile Launcher

Table 2

System Use Designators

System Use Designator Number	System Use
1	Air
2	Water
3	Rough Terrain
4	Dragged/Stationary
5	Roads
6	All Terrain
7	Air and Dragged/Stationary (missile)

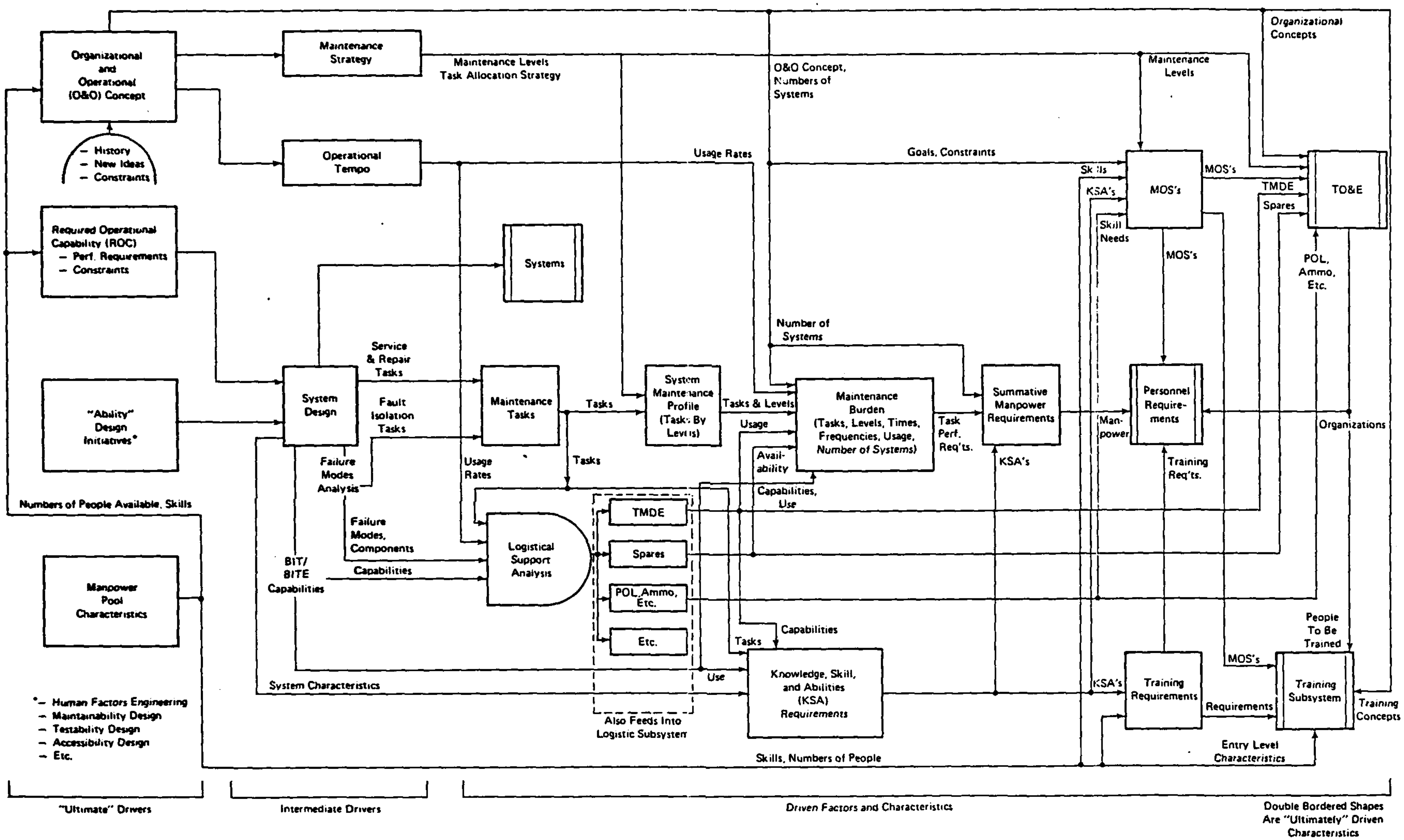

Figure 1. Maintenance Driver Factors Model

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